Aalto University
School of Business

CROSS-SECTIONAL RETURN SEASONALITIES AND INTRA-INDUSTRY OVERREACTION TO EARNINGS SEASONALITIES

Master's Thesis
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Master's Programme in Finance
Spring 2018

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Abstract of master's thesis

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Title of thesis Cross-sectional return seasonalities and intra-industry overreaction to earnings seasonalities	
Degree Master of Science in Economics and Business Administration	
Degree programme Finance	
Thesis advisor(s) Peter Nyberg	
Year of approval 2018	**Number of pages** 55 **Language** English

Abstract

Recent asset pricing literature describes prevalent and recurring return seasonalities in both the time series and cross section of stock returns. Most interestingly for this study, Keloharju, Linnainmaa, and Nyberg (2016) document cross-sectional return seasonalities e.g. in individual stocks, well-diversified portfolios, and various anomalies. Furthermore, Chang et al. (2017) document abnormal returns to earnings seasonalities and find evidence for investors failing to properly price information contained in the seasonal patterns of earnings.

This study is the first attempt to combine these seasonality effects and explain at least a part of the prevalent and persistent occurrence of cross-sectional return seasonalities – even after controlling for firms' own earnings announcements – by the joint effect of abnormal returns to earnings seasonalities and investor overreaction to intra-industry information.

The methodology used to achieve the objective of this study consist of three main sets of methods: Firstly, to calculate cross-sectional return seasonalities, I follow the methodology presented by Keloharju, Linnainmaa, and Nyberg (2016). Secondly, to calculate abnormal returns to earnings seasonalities, I follow the methodology presented by Chang et al. (2017). Finally, to calculate overreaction to intra-industry earnings announcements, I base by methodology to that of Thomas and Zhang (2008). Quarterly earnings data used in the analyses come from Compustat Fundamentals Quarterly file. Monthly and daily stock return data come from Center for Research in Securities Prices (CRSP).

Despite the strong theoretical foundation as well as promising baseline results, the main results of this study are inconclusive: I find that cross-sectional return seasonalities in industry portfolios are lower in magnitude when the effect of intra-industry overreaction to earnings seasonalities is taken into account. Even though this effect is limited, I find certain indications for the importance of intra-industry overreaction in explaining seasonalities in the cross section of stock returns.

This study contributes to the existing literature in two main ways: It structures the theoretical reasoning behind this potential explanation for cross-sectional return seasonalities. Furthermore, it presents the basic methodology for further testing this potential explanation in the future utilizing even enhanced methods.

Keywords asset pricing, cross-sectional return seasonalities, abnormal return, earnings seasonalities, investor overreaction

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Maisterintutkinnon tutkielman tiivistelmä

Tekijä Markus Weckman

Työn nimi Kausivaihtelu osaketuottojen poikkileikkauksessa ja toimialojen sisäinen ylireagointi tulosten kausivaihteluun

Tutkinto Kauppatieteiden maisterin tutkinto

Koulutusohjelma Rahoitus

Työn ohjaaja(t) Peter Nyberg

Hyväksymisvuosi 2018 **Sivumäärä** 55 **Kieli** Englanti

Tiivistelmä

Tuoreet tutkimukset osakkeiden hinnoittelusta kuvaavat laajalle levinneitä ja toistuvia kausivaihteluja sekä osaketuottojen aikasarjassa että poikkileikkauksessa. Tämän tutkielman kannalta mielenkiintoisin näistä on Keloharjun, Linnainmaan and Nybergin (2016) löydös, jonka mukaan tuottojen kausivaihteluja esiintyy esimerkiksi yksittäisten osakkeiden, hyvin hajautettujen salkkujen ja monien anomalioiden poikkileikkauksissa. Tämän lisäksi Chang et al. (2017) dokumentoivat ylituottoja yritysten tulosten kausivaihteluun sijoittamisesta ja löytävät näyttöä sille, että sijoittajat eivät onnistu hinnoittelemaan oikein tietoa, joka sisältyy kausivaihteluun yritysten tuloksissa.

Tämä tutkielma on ensimmäinen, joka yrittää yhdistää nämä kaksi kausivaihteluilmiötä ja selittää vallitsevaa ja sitkeää kausivaihtelua osaketuottojen poikkileikkauksessa (jopa yritysten omien tulosjukistusten kontrolloinnin jälkeen) kahden tekijän yhteisvaikutuksena: ylituotot yritysten tulosten kausivaihteluun sijoittamisesta ja sijoittajien ylireagointi toimialakohtaiseen informaatioon.

Tämän tutkielman tavoitteen saavuttamiseksi käytettävä metodologia koostuu kolmesta pääosasta: Ensinnäkin, laskettaessa kausivaihteluja osakkeiden tuottojen poikkileikkauksessa käytän Keloharjun, Linnainmaan ja Nybergin (2016) esittämää metodologiaa. Toiseksi, laskettaessa ylituottoja yritysten tulosten kausivaihteluun sijoittamisesta käytän samaa metodologiaa kuin Chang et al. (2017). Kolmanneksi, laskettaessa sijoittajien ylireagointia toimialakohtaisiin tulosjulkistuksiin pohjaan menetelmäni metodologiaan, jonka ovat esittäneet Thomas ja Zhang (2008). Analyyseissä käytetty data liittyen yritysten osavuosikatsauksiin tulee Compustat Fundamentals Quarterly –tietokannasta. Osakkeiden kuukausi- ja päivätuottodata sen sijaan tulee Center for Research in Securities Prices (CRSP) –tietokannasta.

Huolimatta vahvasta teoreettisesta pohjasta ja lupaavista alustavista tuloksista tämän tutkielman päätulokset eivät ole ratkaisevia: Teen löydöksen, jonka mukaan kausivaihtelut toimialasalkkujen tuottojen poikkileikkauksessa ovat pienempiä, kun toimialojen sisäinen sijoittajien ylireagointi yritysten tulosten kausivaihteluun otetaan huomioon. Vaikka tämä löydös on rajattu, tutkielmani tuo esiin tiettyjä viitteitä toimialojen sisäisen sijoittajien ylireagoinnin tärkeydestä selitettäessä kausivaihteluja osaketuottojen poikkileikkauksessa.

Tämä tutkielma kontribuoi kahdella päätavalla olemassa olevaan kirjallisuuteen osakkeiden hinnoittelusta: Ensinnäkin, se strukturoi teoreettisen päättelyn, jonka pohjalle tämä mahdollinen selitys kausivaihtelulle osaketuottojen poikkileikkauksessa rakentuu. Lisäksi, se muotoilee perusmetodologian, jonka pohjalta tätä mahdollista selitystä voidaan testata tulevaisuudessa käyttäen entisestään parannettuja menetelmiä.

Avainsanat osakkeiden hinnoittelu, kausivaihtelu osaketuottojen poikkileikkauksessa, ylituotto, tulosten kausivaihtelu, sijoittajien ylireagointi

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1. Introduction

> Evidently, people respond differently when given no evidence and when given worthless evidence. When no specific evidence is given, prior probabilities are properly utilized; when worthless evidence is given, prior probabilities are ignored.
>
> —Amos Tversky and Daniel Kahneman (1974)

Recent asset pricing literature describes prevalent and recurring return seasonalities in both the time series and the cross section of stock returns. For example, Heston and Sadka (2008) present a new pattern within the cross section of expected stock returns: individual stocks tend to have relatively high (or low) returns every year in the same calendar month. In addition to cross-sectional return seasonalities in individual stocks, Keloharju, Linnainmaa, and Nyberg (2016) document similar phenomena in well-diversified portfolios, various anomalies, commodities, international stock market indices, and at the daily frequency. Regarding time-series seasonalities, Chang et al. (2017) re-document the empirical pattern of firms having higher stock returns around earnings announcements covering periods of seasonally higher sales, first documented by Salamon and Stober (1994), and present evidence of abnormal returns consistent with markets failing to properly price information contained in the seasonal patterns of earnings.

Chang et al. (2017) consider the possibility of positive seasonality firms, i.e. firms announcing earnings from a quarter with consistently higher earnings relative to other quarters, having higher exposure to different risk factors in ways that vary over the year (as in the theoretical aggregation mechanism proposed by Keloharju, Linnainmaa, and Nyberg (2016)). Their results indicate that time-varying loadings on standard risk factors do not explain the abnormal return to earnings seasonalities. However, they note that it is difficult to rule out all possible variations on risk-based explanations that involve time-varying expected returns.

Based on the empirical results and theoretical hypotheses of Keloharju, Linnainmaa, and Nyberg (2016) on the one hand and those of Chang et al. (2017) on the other hand, it appears that these seemingly closely-related seasonality effects stem from different sources that remain at least partly unexplained.

The objective of this study is to combine these seasonality effects and explain at least a part of the prevalent and persistent occurrence of return seasonalities by the joint effect of behavioral biases leading to abnormal returns to earnings seasonalities and investor overreaction to intra-industry information. In other words, I aim to show that predictable earnings seasonalities of prominent firms in each industry have an abnormal return effect on other firms in the same industry leading to systematic seasonalities in the cross-section of stock returns. To achieve this objective, I utilize the findings and methodology of Thomas and Zhang (2008), who document this intra-industry bias in investor behavior around earnings announcements.[1]

To clarify the thought process leading to the objective of my thesis, I explain in more detail the theoretical foundation and logical continuum behind my two main hypotheses: My first main hypothesis (H_1) is based on the findings of Chang et al. (2017) and Keloharju, Linnainmaa, and Nyberg (2016) regarding seasonality effects in the cross section of stocks. Firstly, Chang et al. (2017) find that firms earn significant abnormal returns in months when they are likely to announce earnings from a positive seasonality quarter. Secondly, Keloharju, Linnainmaa, and Nyberg (2016) find that portfolios formed based on industry classification exhibit cross-sectional return seasonalities on annual lags. Based on these findings, my first main hypothesis is as follows:

H_1: *Firms in the same industry exhibit earnings seasonality patterns that are positively correlated.*

My second and most important main hypothesis (H_2) is based on my first main hypothesis, as well as the findings of Chang et al. (2017) regarding drivers of seasonal patterns in earnings and those of Thomas and Zhang (2008) regarding intra-industry overreaction.

[1] To be precise, investor reactions to individual earnings announcements of other firms are not inherently biased towards overreaction. However, Thomas and Zhang (2008) find that, as stock prices of firms announcing their earnings are adjusted via a series of positively correlated price movements related to earnings of earlier announcers in the industry, cumulative reactions tend towards overreaction. Based on this, the notion of overreaction is used throughout this study.

Firstly, based on my first main hypothesis, I assume that firms in the same industry exhibit earnings seasonality patterns that are positively correlated. Secondly, as Chang et al. (2017) find that industry factors are a significant driver of seasonal patterns in earnings, I expect different industries to exhibit different earnings seasonality patterns. Finally, Thomas and Zhang (2008) find that investors overreact to industry-specific news released early in the earnings season because they are continuously surprised by firms in the same industry reporting earnings surprises that are predictably positively correlated. This eventually leads to price reversals when firms actually announce their own earnings. Based on these findings, my second main hypothesis is as follows:

H_2: *Cross-sectional return seasonalities in industry-sorted portfolios are explained by the joint effect of positive correlation in intra-industry earnings seasonalities and investor overreaction to industry-specific earnings announcement information.*

This hypothesis of intra-industry overreaction to earnings seasonalities stemming from judgmental heuristics of Tversky and Kahneman (1974) is similar in quality to the findings of Giannetti and Wang (2016), who show that after the revelation of corporate fraud in a given U.S. state, household stock market participation in that state decreases also in nonfraudulent firms. Furthermore, my hypothesis aligns with notions of Lewellen (2002) about excess covariance among stocks. The theoretical model he proposes to explain excess covariance is consistent with investors mistakenly believing that news about one firm contains information about other stocks.

Despite the strong theoretical foundation as well as promising baseline results, the main results of this thesis are inconclusive: I find that portfolios formed based on industry classification earn positive abnormal returns to earnings seasonalities, even though the results are only marginally significant. Furthermore, I find that cross-sectional return seasonalities in industry portfolios are lower in magnitude when the effect of intra-industry overreaction to earnings seasonalities is accounted for. Even though this effect is limited, there are indications for the importance of intra-industry overreaction in explaining seasonalities in the cross section of industry portfolios. Firstly, the average alpha for return seasonalities in industry portfolios decreases significantly after adjusting returns for intra-industry overreaction to earnings seasonalities. Secondly, when regressing return seasonalities against earnings seasonalities using intra-industry overreaction adjusted returns, the explanatory power of earnings seasonalities in industry portfolios strengthens materially compared to unadjusted returns and achieves marginal statistical significance.

This study is the first attempt to combine return and earnings seasonality effects using a behavioral framework of intra-industry investor overreaction. Despite providing only inconclusive evidence and marginally significant results on relations between these three phenomena, it contributes to the existing literature by structuring the theoretical reasoning behind this potential explanation as well as by presenting the basic methodology for further testing my main hypotheses. In conclusion, intra-industry overreaction to seasonally recurring firm-events, such as earnings announcements, potentially provides at least a partial explanation for pervasive and persistent cross-sectional return seasonalities. However, further research utilizing enhanced methods is needed to shed more light on this explanation.

The remainder of the paper is organized as follows. Section 2 discusses the existing literature relevant to this study. Section 3 depicts the data. Section 4 describes the methodology. Section 5 presents the main results. Section 6 concludes.

2. Existing literature

2.1 Cross-sectional return seasonalities

Heston and Sadka (2008) present a new pattern within the cross section of expected stock returns: stocks tend to have relatively high (or low) returns every year in the same calendar month. This annual cross-sectional autocorrelation pattern lasts up to 20 annual lags and explains an economically and statistically significant magnitude of the cross-sectional variation in average stock returns. In addition, they document that the seasonality pattern is independent of size, industry, earnings announcements, dividends, and fiscal year. Interestingly for my thesis, even though the difference in seasonalities between earnings announcement months and other months is insignificantly different from zero, seasonalities seem to be stronger in earnings announcement months.

Heston and Sadka (2008) also find that volume and volatility exhibit similar seasonal patterns as returns. Even though seasonalities in volumes and volatilities do not explain the seasonality in returns, the persistence of volume seasonalities after controlling for most salient firm-events, such as earnings announcement and dividend distribution months, might be evidence for some sort of intra-industry overreaction effects.[2]

In their later paper, concerning the international evidence for return seasonalities, Heston and Sadka (2010) find that stocks outperforming the domestic market in a particular month continue to outperform the domestic market in that same calendar month for up to five years. This pattern appears in Canada, Japan, and 12 European countries. As in their earlier paper, they find that these abnormal seasonal returns remain after controlling for size, beta, and value, using global or local risk factors. In addition, the strategies are not highly correlated across countries, which suggests that they do not reflect return premiums for systematic global risk.

[2] Appendix 1 plots volume seasonalities for individual stocks. Appendix 2 plots volume seasonalities for individual stocks excluding earnings announcement and dividend distribution months.

Keloharju, Linnainmaa, and Nyberg (2016) document return seasonalities in anomalies, commodities, international stock market indices, and at the daily frequency. Furthermore, they find that seasonalities overwhelm unconditional differences in expected returns. In addition, the correlations between different seasonality strategies are modest, suggesting that they emanate from different systematic factors. The results of Keloharju, Linnainmaa, and Nyberg (2016) suggest that seasonalities are not a distinct class of anomalies that requires explanation of its own. Instead, they are intertwined with other return anomalies through shared systematic factors. In other words, the seeming disconnect between seasonalities in individual stock returns and those in factor premiums, documented by Heston and Sadka (2008), is due to the fact that none of the factors alone is responsible for the seasonal patterns in individual stocks. Rather, individual stocks aggregate seasonalities across the risk factors. For example, highly interesting for my thesis is their finding that the seasonality effect is rather strong in well-diversified industry-sorted portfolios (formed based on 17 Fama-French industries). Furthermore, they show that seasonalities in industry-sorted portfolios explain to significant extent the seasonalities in individual stock returns.

Past research has extensively studied seasonalities in asset returns. While Heston and Sadka (2008, 2010) and Keloharju, Linnainmaa, and Nyberg (2016) study seasonalities in the cross section of asset returns, most of the extant literature is about time-series seasonalities. For example, Kamstra, Kramer, and Levi (2003) investigate the role of seasonal affective disorder (SAD) in the seasonal time-variation of stock market returns. Using data from numerous stock exchanges in both hemispheres and controlling for well-known market seasonals as well as other environmental factors, they show that stock returns are significantly related to the amount of daylight through the fall and winter. Moreover, they find that higher latitude markets show more pronounced SAD effects. Garrett, Kamstra, and Kramer (2005) build on this evidence and find that a conditional capital asset pricing model (CAPM) that allows the price of risk to vary in relation to seasonal variation in the length of day fully captures the SAD effect. They point out that this result is consistent with the notion that the SAD effect arises because of the heightened risk aversion that comes with seasonal depression. Even though these papers have different approach on return seasonalities, they provide important insight on explaining the fundamental reasons that cause seasonal variation in risk factors and security returns.

Whereas various theoretical frameworks and mechanisms have been devised to explain time-varying seasonalities in stock returns, Keloharju, Linnainmaa, and Nyberg (2016) are the first ones to present a theoretical model that explains the mechanism aggregating seasonalities across different risk factors. Firstly, they show that any seasonality in factor risk premium always gets transferred to the cross section of security returns if factor loadings vary across securities. Secondly, they show that this result is not confined to a single-factor model and that returns aggregate seasonalities stemming from risk premiums if securities are exposed to multiple risk factors. Thirdly, they show, how dispersion in factor loadings determines the amount of seasonalities in the cross section of stock returns.

Keloharju, Linnainmaa, and Nyberg (2016) also consider alternative explanations for return seasonalities. According to these alternative explanations, return seasonalities are either firm specific or stem from autocorrelated return innovations. However, they find strong evidence against both of these alternative explanations.

Building on the findings and theoretical foundation of Keloharju, Linnainmaa, and Nyberg (2016), Bogousslavsky (2016) presents a model of infrequent rebalancing which can explain specific predictability patterns in the time series and cross section of stock returns. He finds evidence for return autocorrelations that are consistent with empirical evidence from intraday and daily returns. In addition, he finds that the cross-sectional variance in expected returns is larger when more traders rebalance. These effects stemming from infrequent rebalancing generate seasonality in the cross-section of stock returns, which can partly help explain empirical evidence presented by Heston and Sadka (2008, 2010) and Keloharju, Linnainmaa, and Nyberg (2016).

2.2 Earnings seasonalities, stock returns, and investor overreaction

Chang et al. (2017) present evidence of abnormal returns consistent with markets failing to properly price information contained in the seasonal patterns of earnings. The authors find that companies earn significant abnormal returns in months when they are likely to announce earnings from a positive seasonality quarter (i.e., a quarter with consistently higher earnings relative to other quarters). Their findings replicate with more recent data the empirical pattern, whereby firms have higher stock returns around earnings announcements covering periods of seasonally higher sales, which was first documented by Salamon and Stober (1994).

In addition, Chang et al. (2017) show that mispricing, rather than a risk-based story, better explains the seasonal patterns in returns. According to the authors, the earnings seasonality measure they use makes it unlikely that abnormal earnings announcement returns are driven by seasonal firms having different fixed loadings on risk factors, as firms tend to cycle through both the long and short legs of the test portfolios.

Regarding the mispricing story, Chang et al. (2017) find positive evidence of investor mistakes. They find consistently positive analyst forecast errors in positive seasonality quarters implying analysts taking seasonality into account, but not completely correcting for seasonal changes. They continue by stating that to the extent that individual investors make the same mistakes, or take analysts' mistaken forecasts at face value, the portfolio returns are consistent with mispricing rather than risk-based explanation. This is highly plausible as So (2012) provides evidence that investors overweight analyst forecasts by demonstrating that stock prices do not fully reflect predictable components of analyst errors. In addition, Chang et al. (2017) find evidence for the effects of seasonality being due to investors overweighting recent earnings when forming estimates of future earnings.

Furthermore, Chang et al. (2017) conduct various robustness tests to rule out other time-series effects within the firm. Abnormal returns to predictable earnings seasonalities survive the various controls for other determinants of time-series effects suggesting that earnings seasonality is not some general driver of returns, as it does not forecast higher returns outside of earnings months. Overall, their results are consistent with investors having an excessive focus on recent events, leading to insufficient attention to longer-term patterns in earnings.

Closely related to the excessive focus on recent events, Thomas and Zhang (2008) find evidence for an expectational bias in which investors overestimate the intra-industry implications of early announcers' earnings for late announcers' earnings, and that the overestimation is corrected when late announcers actually disclose their earnings. In other words, investors mistakenly believe that each prior earnings announcement contains new and relevant information for late-announcing firms leading to overreaction to intra-industry information. These findings are consistent with those of Barber et al. (2013), who document that earnings announcement premium actually accrues in the pre-announcement period. Thomas and Zhang (2008) consider the possibility of their results being due to some other explanation than investor irrationality, but find no supporting evidence for this. Instead, they provide an irrational investor explanation for the apparent investor overreaction, whereby investors are surprised by firms in the same industry reporting earnings surprises that are predictably positively correlated. In the case of late-announcing firms, their stock prices are adjusted via a series of positively correlated price movements that potentially causes them to overestimate the price that reflects the earnings report they eventually disclose. This explanation is consistent with bias caused by investors relying on representativeness heuristic.

2.3 Heuristics and biases: representativeness, availability, and anchoring

Tversky and Kahneman (1974) show that people rely on a limited number of heuristic principles, which reduce the complex tasks of assessing probabilities and predicting values to simpler judgmental operations. Their seminal article describes three heuristics that are employed in making judgments under uncertainty: (i) *representativeness*, (ii) *availability*, and (iii) *anchoring*. In addition, they enumerate biases to which these heuristics lead and discuss applied and theoretical implications of their observations.

Firstly, according to Tversky and Kahneman (1974), *representativeness* heuristic is usually employed when people are asked to judge the probability that an object or event A belongs to class or process B. Thus, in answering such questions, probabilities are typically evaluated by the degree to which A is representative of B, i.e., by the degree to which A resembles B. They describe various biases this approach to the judgment of probability leads to, as representativeness is not influenced by several factors that should affect judgments of probability. These biases include (i) insensitivity to prior probability of outcomes, (ii) insensitivity to sample size, (iii) misconceptions of chance, (iv) insensitivity to predictability, (v) the illusion of validity, and (vi) misconceptions of regressions. The findings of Thomas and Zhang (2008) are a relevant example of biases in financial markets stemming from representativeness heuristic: investors believe to a too high a degree that earnings announcement of firm B contains relevant information about upcoming earnings announcement of firm A if the two operate in the same industry and thus at least seemingly resemble each other.

Furthermore, Tversky and Kahneman (1974) state that there are situations in which people assess the frequency of a class or the probability of an event by the ease with which instances or occurrences can be brought to mind. They call this judgmental heuristic *availability*. As availability is affected by factors other than frequency and probability, reliance on it in judgments of probabilities leads to predictable biases. These include: (i) biases due to the retrievability of instances, (ii) biases due to the effectiveness of a search set, (iii) biases of imaginability, and (iv) illusory correlation. Even though not directly linked to this study, the findings of Hartzmark and Shue (2017) regarding contrast effects in financial markets provide an illustrative example of this effect in a relevant context. They find that earnings surprises from earnings announced just before (on the previous day or earlier in the same day) the earnings announcement of firm A have an inverse effect on how earnings of firm A are perceived. In other words, earnings of firm A are mistakenly perceived as more impressive if the earnings surprises from the previous announcements were negative and less impressive if they were positive.

Finally, Tversky and Kahneman (1974) argue that, in many situations, people make estimates by starting from an initial value, or starting point (suggested by the formulation of the problem or obtained as a result of a partial computation) that is adjusted to yield the final answer. Based on various empirical studies, they show that adjustments are typically insufficient yielding different estimates, which are biased toward the initial values. They call this judgmental heuristic *anchoring*. The biases emanating from this phenomenon include: (i) insufficient adjustment, (ii) biases in the evaluation of conjunctive and disjunctive events, and (iii) anchoring in the assessment of subjective probability distributions. The findings of Chang et al. (2017) regarding abnormal returns to earnings seasonalities act as a relevant illustration of biases stemming from this heuristic: even though sophisticated investors understand that earnings of firms exhibit annually recurring seasonalities, they still anchor themselves to earnings of previous quarters and consequently fail to adjust correctly for predictable seasonality patterns in earnings.

In discussing applied and theoretical implications of their observations, Tversky and Kahneman (1974) note that the biases they described are not attributable to motivational effects such as wishful thinking or the distortion of judgments by payoffs and penalties. They continue that several of the judgment errors occurred despite the fact that subjects were encouraged to be accurate and were rewarded for the correct answers. Furthermore, Tversky and Kahneman (1974) state that the reliance on heuristics and the prevalence of biases emanating from them are not restricted to naïve subjects. Instead, experienced researchers and other sophisticated judges are also prone to the same biases when they think intuitively.

Even though the heuristics described lead to systematic and predictable errors, they are usually highly economical and typically effective. Thus, Tversky and Kahneman (1974) conclude that a better understanding of these heuristics and of the biases to which they lead could improve judgments and decisions in situations of uncertainty.

Heuristics and biases described by Tversky and Kahneman (1974) are not explicitly discussed when methodology and results of this study are presented. However, throughout this study, their findings and theoretical formulations act as a framework based on which investor behavior leading to cross-sectional return seasonalities in industry portfolios is being explained.

3. Data

To conduct my analyses, I use data from three main sources. Firstly, the data for earnings as well as all other accounting data come from the Compustat Fundamentals Quarterly file. I use quarterly accounting data from January 1973 through September 2017. The key reasons for selecting this time-period are that Compustat Fundamentals Quarterly file includes earnings announcement dates since the third calendar quarter of 1971 and was expanded to cover NASDAQ stocks in January 1973. Accounting data before November 1978 are only used as a right-hand-side variable.

Secondly, monthly and daily stock return data come from the Center for Research in Securities Prices (CRSP)[3]. In my tests, I only use the common stock (CRSP share codes 10 or 11) of firms listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), or NASDAQ, and exclude stocks with missing market capitalization at the end of the previous month. To avoid survivorship bias, I use CRSP delisting returns. Following the usual convention to account for the delisting bias in CRSP data[4], I use a delisting return of -30%, if a delisting return is missing and the delisting is performance-related. To account for the availability of relevant accounting data, I use returns from November 1978 through September 2017 in cross-sectional return seasonality regressions and earnings seasonality calculations. However, for the right-hand-side variables, I use monthly and daily returns going back to November 1958.

Thirdly, industry classifications as well as excess market return, risk-free rate, and returns for small-minus-big (SMB), high-minus-low (HML), and up-minus-down (UMD) portfolios are obtained from Kenneth French's data library. Throughout this study, I use the classification that divides firms into 17 industry portfolios.

[3] To combine these two main sources of data and account for differing company identifier standards in them, I use CRSP/Compustat Merged Database.

[4] See Shumway (1997).

4. Methodology

4.1 Cross-sectional return seasonalities

To calculate cross-sectional return seasonalities, I follow the methodology of Keloharju, Linnainmaa, and Nyberg (2016). Subsequent return seasonality calculations differ in their exact methodology but all of them share the same basic principle – predicting stock returns in month t with stock returns at annual lags for up to 20 years. In addition to this basic principle, all return seasonality calculations share two key steps in their methodology: In each monthly sample, I only include stocks with a minimum of five years of return data available as of month t. In addition, as stocks differ in their availability of historical data, I demean stock returns in each monthly cross section before calculating the returns. Subsequent steps in different return seasonality calculations will be explained in detail when results are discussed in Section 5.

4.2 Earnings seasonalities

To calculate abnormal returns to earnings seasonalities, I follow the methodology of Chang et al. (2017). First, to construct the measure of predicted earnings seasonality in quarter q, I use earnings data from the previous five years, i.e. quarters $q-23$ through $q-4$. The earnings measure used in all the earnings seasonality calculations of this paper is earnings per share (excluding extraordinary items) adjusted for stock splits.[5]

After this, for the firms with non-missing values for all quarters $q-23$ through $q-4$, I rank the 20 quarters of earnings data from largest to smallest. The main measure of interest, *earnrank*, is the average rank of the same fiscal quarter earnings as the upcoming announcement from previous years. In other words, for quarter q, *earnrank* is the average rank of quarters $q-4$, $q-8$, $q-12$, $q-16$, and $q-20$. As in Chang et al. (2017), a high value of *earnrank* stands for historically higher earnings in the current quarter of the year

[5] As Chang et al. (2017) show, abnormal returns to earnings seasonalities are robust to alternative measures of earnings, and thus the choice of this specific earnings measure does not affect my results.

than in other quarters, a low value of *earnrank* for historically lower earnings in the current quarter, and a value in the middle of the distribution of *earnrank* for earnings that have historically been randomly distributed. As the reader can observe and as Chang et al. (2017) also note, *earnrank* is rather simple to construct, can be easily replicated, and is transparent in what is being measured. Furthermore, it avoids certain complicating empirical issues, such as the existence of negative earnings, large outliers, and trends in overall earnings growth.

Following the calculation of *earnrank*, I predict whether a firm will have an earnings announcement in month *t*. To do this, I check whether a firm had an earnings announcement 12 months before, and do not condition ex post whether the same firm actually had an earnings announcement in month *t*, as changed timing of the announcement may contain relevant information for returns.[6]

Finally, I sort all the firms with predicted earnings announcement in month *t* to top and bottom portfolios based on *earnrank*. Exact sorting methods differ between earnings seasonality calculations for individual stocks and industry portfolios and they will be explained in detail when results are discussed in Section 5. As Chang et al. (2017) point out, because firms with predicted earnings announcement in the month in question in general enjoy positive abnormal returns[7], the main measure of interest in interpreting earnings seasonalities is the return difference between the top and the bottom portfolios.

4.3 Intra-industry overreaction to earnings announcements

The methodology for calculating intra-industry overreaction to earnings announcements is based on the methodology of Thomas and Zhang (2008) to calculate investor overreaction to industry-specific news. I start by calculating a proxy measure for the prominence of a firm within its industry. To do this, I take firm *j* and regress past five years of historical monthly returns of all the other firms in the same industry against historical returns of firm *j*. Specifically, I regress:

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[6] See Frazzini and Lamont (2007). For example, delays in earnings announcements are often due to bad news for investors.

[7] Frazzini and Lamont (2007) document a positive earnings announcement premium.

$$r_{i,[t-60,t-1]} = a_{j,i} + b_{j,i}\, r_{j,[t-60,t-1]} + e_{j,i}. \tag{1}$$

After this, I take the average beta coefficient from these regressions against the returns of firm *j* to obtain a measure of historical prominence of the firm in the industry. I then repeat this procedure and use each firm in turn as the right-hand side variable in these regressions. For each of the 17 Fama-French industries, I define as industry leaders the firms which have the highest average betas from these regressions against historical returns of other firms in the same industry.

To account for the changing nature of intra-industry prominence of firms, I rerun these regressions every five years using monthly return data from the previous five years and obtain new industry leaders to be used for the next five years. Due to this procedure, I also require each industry leader to have non-missing return data for the next five years after month *t*.

After this, I isolate the effect of the industry leaders' earnings announcements by dividing monthly return coefficient of each firm in month *t* with its own daily return coefficient on the industry leaders' earnings announcement date *d* (see Equation (2)). These adjusted monthly returns are then used in the subsequent return and earnings seasonality calculations.

$$r_{adjusted,i,t} = (1 + r_{i,t}) \,/\, (1 + r_{i,d}) - 1 \tag{2}$$

In calculating return and earnings seasonalities adjusted for intra-industry overreaction, I use a few different specifications for the number of industry leaders and the length of earnings announcement adjustment period. These specifications and the exact methodology used in different analyses will be explained in more detail when results are discussed in Section 5.

5. Results

Results from my analyses are split in two main sections: Section 5.1, on the one hand, contains the baseline results for cross-sectional return seasonalities, earnings seasonalities, and their combination. Section 5.2, on the other hand, presents the results for the same phenomena after controlling for intra-industry overreaction. In both sections, I will discuss in more detail the methodology used to obtain the presented results.

5.1 Baseline results for cross-sectional return seasonalities and earnings seasonalities

Baseline results for cross-sectional return seasonalities, earnings seasonalities, and their combination are split in three subsections: Firstly, Subsection 5.1.1 presents the baseline results for cross-sectional return seasonalities. Most of the analyses behind these results are at least partial replications of the analyses conducted by Heston and Sadka (2008) and Keloharju, Linnainmaa, and Nyberg (2016). Secondly, Subsection 5.1.2 contains the baseline results for earnings seasonalities. Most of the analyses behind these results at least partially replicate the analyses conducted by Chang et al. (2017). Finally, Subsection 5.1.3 presents the baseline results from combining these two phenomena of interest.

5.1.1 Cross-sectional seasonalities in individual stock and industry portfolio returns

To obtain the baseline results for seasonalities in the cross section of individual stocks, I follow the methodology of Keloharju, Linnainmaa, and Nyberg (2016). As mentioned in Section 4, I start by demeaning stock returns in each monthly cross section by subtracting the cross-sectional average monthly return from each firm's raw return in the same month.

To obtain my first set of baseline results for cross-sectional seasonalities in individual stock returns, I continue by regressing each firm's demeaned monthly returns in month t against their returns in months $t - k,$ with k ranging from 1 to 240 months. Figure 1 presents the average slope coefficients from these regressions and replicates the annual seasonality pattern in the cross section of individual stock returns first documented by Heston and Sadka

(2008) and further extended by Keloharju, Linnainmaa, and Nyberg (2016). Cross-sectional seasonalities in the cross section of individual stocks are remarkably strong: 19 out of 20 annual lags have a positive coefficient and 14 of these positive coefficients are accompanied by a *t*-value indicating statistical significance at the 5% level. In addition, slope coefficients of annual lags have on average a positive value of 0.67%.

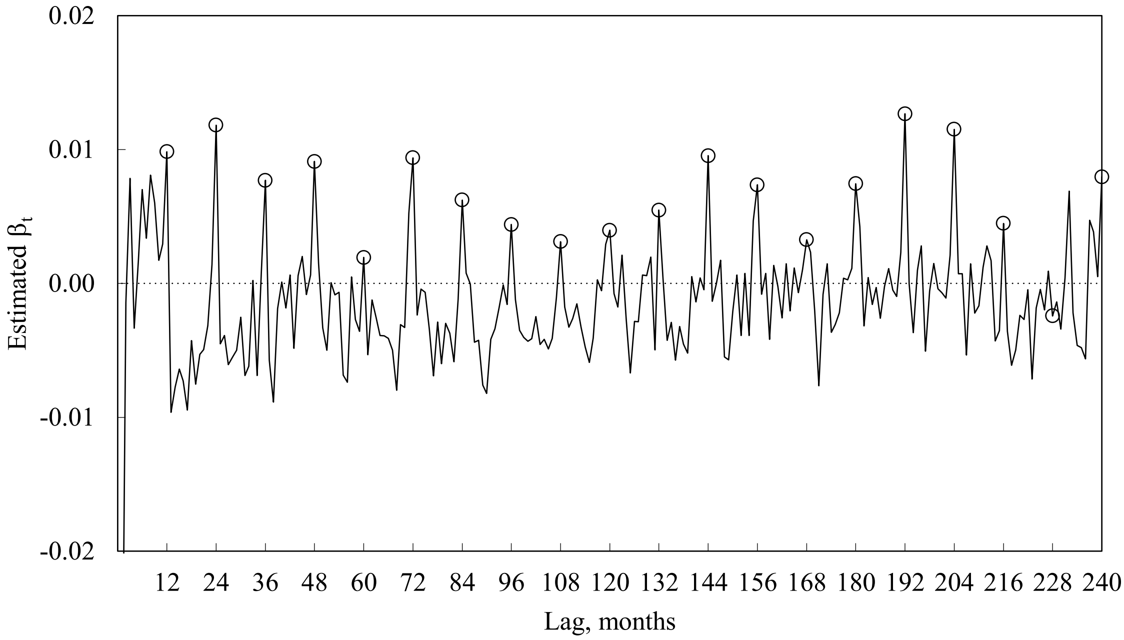

Figure 1: Seasonalities in individual stock returns

This figure plots slope coefficients from univariate Fama and MacBeth (1973) regressions of month t returns against month $t - k$ returns, $r_{i,t} = a_t + b_t r_{i,t\text{-}k} + e_{i,t}$, with k ranging from 1 to 240 months. The circles denote estimates at annual lags. The regressions use monthly data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

Figure 2 replicates the analyses used to obtain slope coefficients in Figure 1, but excludes firms with earnings announcement in the given month. Even when excluding such seasonally recurring firm-events as earnings announcements, return seasonalities remain remarkably strong, thus confirming the findings of Heston and Sadka (2008)[8]. Again, 19 out of 20 annual lags have a positive slope coefficient. Furthermore, 12 of these positive coefficients remain

[8] Heston and Sadka (2008) find that return seasonalities also survive after controlling for other recurring firm-events such as dividends.

statistically significant at the 5% level. Average slope coefficient at annual lags also remains almost as strong as in Figure 1 and equals 0.63%.

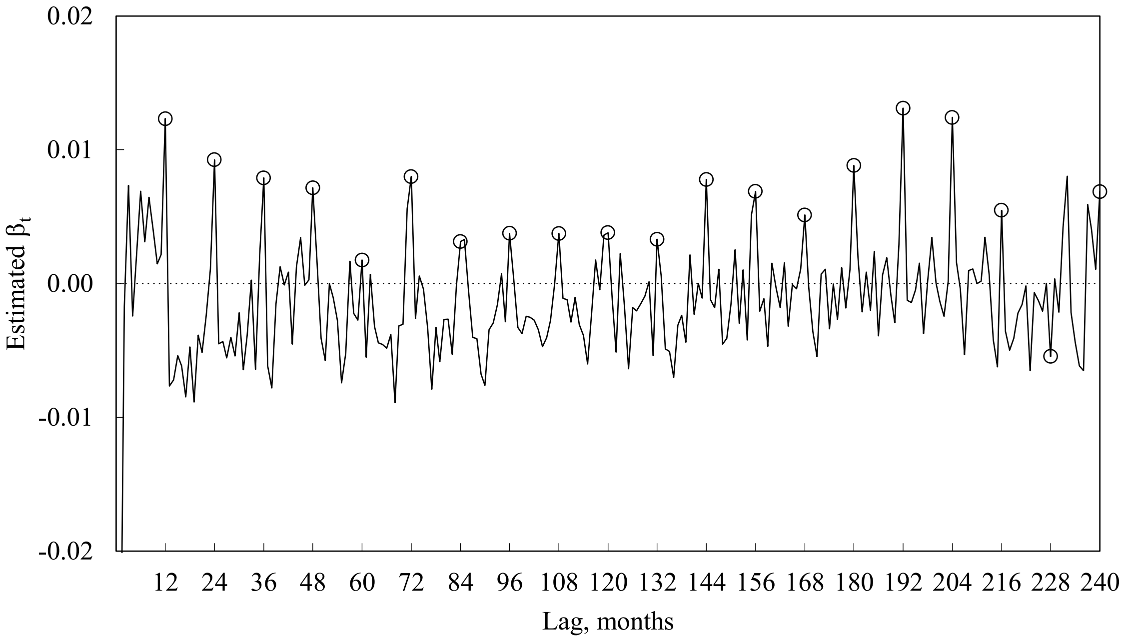

Figure 2: Seasonalities in individual stock return excluding firms with earnings announcement months

This figure plots slope coefficients from univariate Fama and MacBeth (1973) regressions of month *t* returns against month *t* – *k* returns, $r_{i,t} = a_t + b_t r_{i,t\text{-}k} + e_{i,t}$, with *k* ranging from 1 to 240 months. The circles denote estimates at annual lags. Methodology used to calculate the slope coefficients is equivalent to that of Figure 1, but the sample excludes firms with earnings announcement in month *t*. The regressions use monthly data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

The next set of baseline results moves us to the main field of interest in this study, i.e. seasonality effects in the cross section of industry portfolios. To obtain cross-sectional seasonalities in industry portfolio returns, I follow a methodology that is almost identical to that used in calculating return seasonalities for individual stocks. The only difference is that, instead of using returns for individual stocks, I use value-weighted returns for industry portfolios formed based on 17 Fama-French industries. Figure 3 presents the results for cross-sectional seasonalities in industry portfolio returns. Even though the annual seasonality pattern is still clearly discernible, the effect is not as strong as in the cross section of individual stock returns. However, 15 out of 20 annual lags are positive and six out of these 15 are statistically significant at the 5% level. As in the case of individual stocks, average coefficient at annual lags is positive and equals 0.22%.

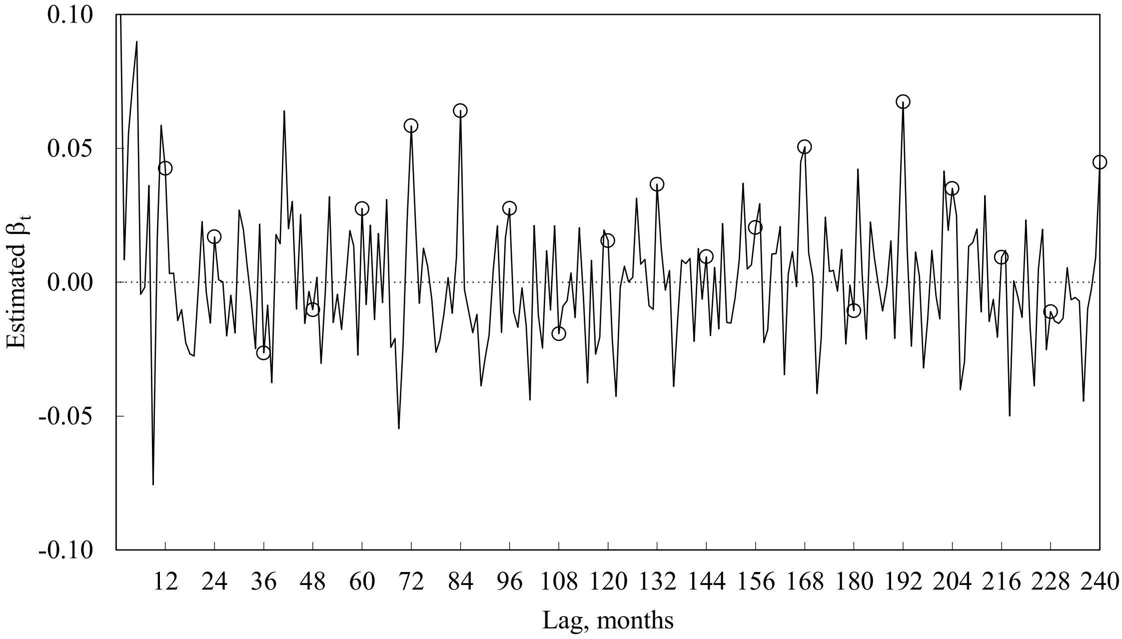

Figure 3: Seasonalities in industry portfolio returns

This figure plots slope coefficients from univariate Fama and MacBeth (1973) regressions of month t returns against month $t - k$ returns, $r_{i,t} = a_t + b_t r_{i,t-k} + e_{i,t}$, with k ranging from 1 to 240 months. The data are returns on 17 industry portfolios formed based on industry classifications on Kenneth French's data library. The circles denote estimates at annual lags. The regressions use monthly data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

Figure 4 continues by presenting seasonalities in industry portfolio returns excluding firms with earnings announcements in the given month. As in Figure 3, annual seasonality pattern remains after excluding the effect of earnings announcements, but the results are not as strong as in the cross section of individual stock returns. However, 14 out of 20 annual lags remain positive and five out of these 14 are still accompanied by a t-value indicating statistical significance at the 5% level. As in the previous results, average slope coefficient remains positive and equals 0.20%.

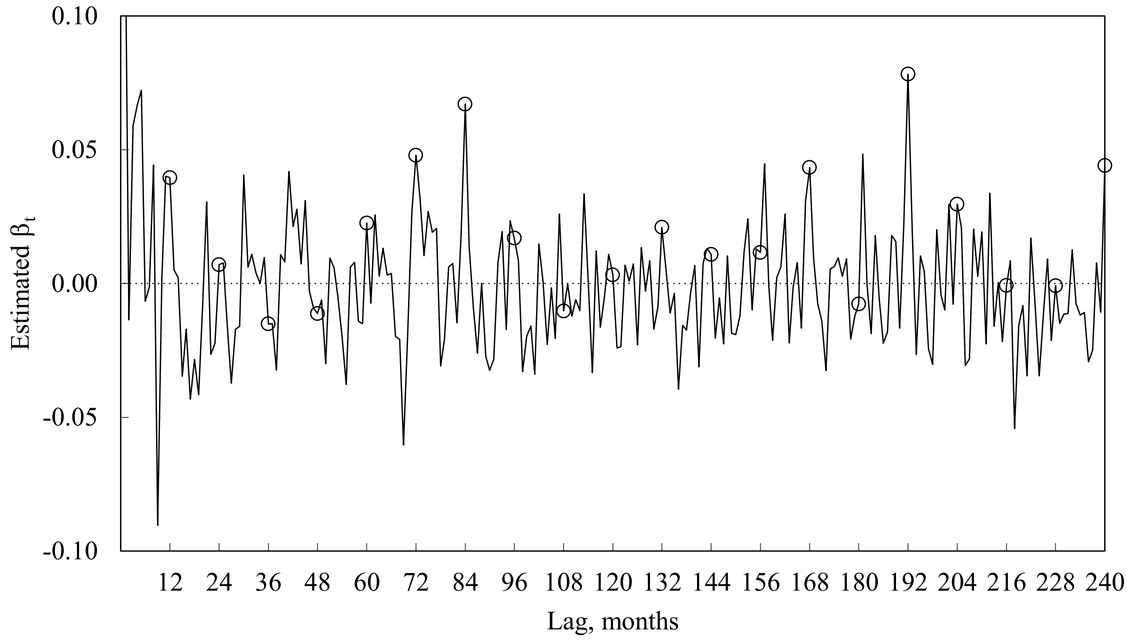

Figure 4: Seasonalities in industry portfolio returns excluding firms with earnings announcement months

This figure plots slope coefficients from univariate Fama and MacBeth (1973) regressions of month t returns against month $t - k$ returns, $r_{i,t} = a_t + b_t r_{i,t-k} + e_{i,t}$, with k ranging from 1 to 240 months. The data are returns on 17 industry portfolios formed based on industry classifications on Kenneth French's data library. Methodology used to calculate the slope coefficients is equivalent to that of Figure 3, but the sample excludes firms with earnings announcement in month t. The circles denote estimates at annual lags. The regressions use monthly data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

The next set of baseline results for cross-sectional return seasonalities approaches this phenomenon from a slightly different angle and calculates the average returns for strategies that invest in the seasonality effect. To calculate these returns for portfolios formed from individual stocks, I use the following methodology presented by Keloharju, Linnainmaa, and Nyberg (2016): First, I calculate the 20-year average same-calendar month and other-calendar month returns[9] for each stock in the sample. Second, in each monthly cross section, I divide firms into ten decile portfolios based on their average same-month and other-month returns. Third, I calculate returns for the same-month and the other-month strategy: Same-month strategy takes a long position in the top decile portfolio and a short position in the bottom decile portfolio based on the 20-year average same-month return. Other-month

[9] In calculating the 20-year average other-calendar month returns, I skip months $t - 11$ through $t - 1$ to correct for one-month return reversal and momentum.

strategy takes a long position in the top decile portfolio and a short position in the bottom decile portfolio based on the 20-year average same-month return.[10] Finally, I calculate the difference between the same-month strategy and the other-month strategy. This difference is the main measure of interest in these calculations as it captures the cross-sectional seasonality effect.

To calculate the returns from seasonality effect for industry portfolios, I follow rather similar methodology: First, I divide firms into industry portfolios based on 17 Fama-French industries. Second, I calculate value-weighted monthly return for each industry portfolio in each monthly cross section. Third, I calculate returns for the same-month and the other-month strategy: Same-month strategy takes a long position in the top-2 industry portfolios and a short position in the bottom-2 industry portfolios based on their 20-year average same-calendar month return. Other-month strategy takes a long position in the top-2 industry portfolios and a short position in the bottom-2 industry portfolios based on their 20-year average other-calendar month return. Finally, as in the case of portfolios formed from individual stocks, I calculate the difference between the same-month strategy and the other-month strategy to capture the cross-sectional seasonality effect.

Panel A of Table 1 presents the average monthly returns and four-factor alphas[11] for individual stock and industry portfolios formed using the aforementioned methodology. As in Figure 1 presented earlier, seasonality effect within the cross section of individual stocks is remarkably strong: Average difference in monthly returns for the same-month and the other-month strategy is 2.00% (*t*-value = 6.92). Furthermore, this result stays almost unchanged when controlling for the factors in Fama and French (1993) three-factor model and momentum, as the difference portfolio achieves an average monthly four-factor alpha of 1.95% (*t*-value = 7.26). As in Figure 3 before, return seasonalities are well-discernible in the cross section of industry portfolio returns, even though they are not as prominent.

[10] Throughout this study, I calculate returns for seasonality portfolios using value-weighted returns. As Keloharju, Linnainmaa, and Nyberg (2016) note, this does not affect the results as return seasonalities are, if anything, stronger when using equal-weighted returns.

[11] Alphas from regressions that control for the factors in Fama and French (1993) three-factor model and momentum.

Average difference in monthly returns for the same-month and the other-month strategy is 0.57% (t-value = 2.01) and average four-factor alpha equals 0.52% (t-value = 1.80).[12]

Panel B of Table 1 presents the same results for individual stock and industry portfolios excluding firms with earnings announcement in the given month. Results are in line with those presented earlier in Figure 2 and Figure 4: Seasonality effect is slightly weakened when calculations exclude earnings announcement months, but the main conclusion remains unchanged. Portfolios formed from individual stocks earn strongly positive and highly significant seasonality returns, whereas industry portfolios earn more modest and marginally significant positive returns.

[12] My results for seasonality effect in industry portfolios differ slightly from those of Keloharju, Linnainmaa, and Nyberg (2016), who document strongly positive and highly significant seasonality returns for industry portfolios. This difference arises from differing time periods: Keloharju, Linnainmaa, and Nyberg (2016) use monthly return data from January 1963 through December 2011, whereas I use data from November 1978 through September 2017.

Table 1: Return seasonalities in individual stocks and industry-sorted portfolios

For individual stocks: First, I calculate the 20-year average same-calendar month and other-calendar month returns for each stock in the sample. Second, in each monthly cross section, I divide firms in ten decile portfolios based on their average same-month and other-month returns. Third, I calculate the return on the same-month and other-month strategy: Same-month strategy takes a long position in the top decile portfolio and a short position in the bottom decile portfolio based on the 20-year average same-month return. Other-month strategy takes a long position in the top decile portfolio and a short position in the bottom decile portfolio based on the 20-year average same-month return. Finally, I calculate the difference between the same-month strategy and other-month strategy. For industry portfolios: First, I divide firms to industry portfolios based on 17 Fama-French industries. Second, I calculate value-weighted monthly return for each industry portfolio in each monthly cross section. Third, I calculate the return on the same-month and other-month strategy: Same-month strategy takes a long position in the top-2 industry portfolios and a short position in the bottom-2 industry based on their 20-year average same-calendar month return. Other-month strategy takes a long position in the top-2 industry portfolios and a short position in the bottom-2 industry portfolios based on their 20-year average other-calendar month return. Finally, as in the case of portfolios formed from individual stocks, I calculate the difference between the same-month strategy and other-month strategy to capture the cross-sectional seasonality effect. To obtain four-factor alphas, I regress the returns of the same-month and other-month strategy as well as their difference against the factors in Fama and French (1993) three-factor model and momentum. The regressions use monthly data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

Panel A: Summary statistics for returns

Set of	Monthly returns and alphas (%) Sort by						*t*-values Sort by					
	Same-month return		Other-month return		Same-other		Same-month return		Other-month return		Same-other	
assets	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α
Individual stocks	1.27	1.38	-0.73	-0.57	2.00	1.95	5.65	6.11	-3.20	-3.57	6.92	7.26
Industry portfolios	0.54	0.53	-0.03	0.01	0.57	0.52	2.48	2.37	-0.13	0.06	2.01	1.80

Panel B: Summary statistics for returns excluding earnings announcement months

Set of	Monthly returns and alphas (%) Sort by						*t*-values Sort by					
	Same-month		Other-month		Same-other		Same-month		Other-month		Same-other	
assets	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α
Individual stocks	1.01	1.12	-0.68	-0.56	1.69	1.69	4.33	4.78	-2.94	-3.25	5.63	5.82
Industry portfolios	0.55	0.66	0.08	0.06	0.47	0.60	2.23	2.62	0.35	0.29	1.41	1.75

5.1.2 Abnormal returns to earnings seasonalities in individual stocks and industry portfolios

As explained in Section 4, I follow the methodology of Chang et al. (2017) to calculate abnormal returns to earnings seasonalities in individual stocks and industry portfolios. More specifically, to obtain the baseline results for earnings seasonality returns in individual stocks, I go through the following steps: First, I calculate the measure of predicted earnings seasonality, *earnrank,* in quarter *q* by ranking the 20 quarters of earnings data from the previous five years from largest to smallest and taking the average rank from the previous years of the same fiscal quarter earnings as the upcoming announcement. Second, I predict whether a firm will have an earnings announcement in month *t* by conditioning on the same firm having an earnings announcement 12 months before. Third, I sort all the firms with predicted earnings announcement in month *t* to quintile portfolios with firms having the highest *earnrank* being in the top quintile portfolio (Q5) and firms having the lowest *earnrank* being in the bottom quintile portfolio (Q1). Fourth, I calculate monthly returns for the quintile portfolios. Finally, I calculate the difference between the top and bottom quintile portfolio to obtain a measure of abnormal returns to earnings seasonalities.

Calculating the baseline results for earnings seasonalities in industry portfolios follows highly similar methodology: First, I calculate the predicted measure of earnings seasonality, *earnrank*, in quarter *q* for each stock. Second, I predict whether a firm will have an earnings announcement in month *t* by conditioning on the same firm having an earnings announcement 12 months before. Third, I divide firms into industry portfolios based on 17 Fama-French industries and calculate the value-weighted average *earnrank* for each industry. Fourth, I sort all industries based on *earnrank* and form two portfolios with top-2 industries being in one and bottom-2 industries being in the other. Fifth, I calculate monthly returns for the top-2 and the bottom-2 portfolios. Finally, I calculate the difference between the top-2 and the bottom-2 industry portfolios to obtain a measure of abnormal returns to earnings seasonalities.

Panel A of Table 2 presents value-weighted and equal-weighted results for these calculations on abnormal returns to earnings seasonalities in individual stocks. As mentioned earlier, stocks with predicted earnings announcement earn highly positive returns on average and this effect is clearly present also in my results. More interestingly, the difference between the top and the bottom quintile returns is also significantly positive with an average value-weighted monthly difference of 0.49% (*t*-value = 2.42). Panel B of Table 2 presents the same results for industry portfolios. As in the case of individual stocks, the average monthly value-weighted difference between the top-2 and the bottom-2 industries is positive and equals 0.40%. However, due to higher volatility in industry portfolios, the difference is not statistically significant (*t*-value = 1.24), even though its direction is in line with earnings seasonality returns in individual stocks. In both panels of Table 2, results are even stronger, when equal weights are used in calculating portfolio returns.

Table 3 completes the baseline results for abnormal returns to earnings seasonalities: Panel A of the table presents the four-factor alphas from regressing earnings seasonality returns for individual stocks against the factors in Fama and French (1993) three-factor model and momentum. Panel B of the same table presents the four-factor alphas for earnings seasonalities in industry portfolios. Results from these regressions indicate that earnings seasonalities are stronger when controlling for some of the most salient factors affecting stock returns. Average monthly four-factor alpha for the value-weighted difference portfolio equals 0.53% (*t*-value = 2.54) for individual stocks, whereas the same figure equals 0.57% (*t*-value = 1.70) for industry portfolios. Again, results are even stronger for equal-weighted portfolios.

To conclude on my first main hypothesis about firms in the same industry exhibiting earnings seasonality patterns that are positively correlated: I find directionally correct yet inconclusive evidence to support this hypothesis. Industry-sorted portfolios tend to earn positive abnormal returns to earnings seasonalities, even though these returns are only marginally significant.

Table 2: Earnings seasonalities and stock returns

For individual stocks: First, I calculate the measure of predicted earnings seasonality, *earnrank*, in quarter q by ranking the 20 quarters of earnings data from the previous five years from largest to smallest and taking the average rank from the previous years of the same fiscal quarter earnings as the upcoming announcement. Second, I predict whether a firm will have an earnings announcement in month t by conditioning on a firm having an earnings announcement 12 months before. Third, I sort all the firms with predicted earnings announcement in month t to quintile portfolios with firms having the highest *earnrank* being in the top quintile portfolio (Q5) and firms having the lowest *earnrank* being in the bottom quintile portfolio (Q1). Fourth, I calculate monthly returns for the quintile portfolios. Finally, I calculate the difference between the top and bottom quintile portfolio to obtain a measure of abnormal returns to earnings seasonalities. For industry portfolios: First, I calculate the predicted measure of earnings seasonality, *earnrank*, in quarter q for each stock. Second, I predict whether a firm will have an earnings announcement in month t by conditioning on a firm having an earnings announcement 12 months before. Third, I divide firms in industry portfolios based on 17 Fama-French industries and calculate the value-weighted average *earnrank* for each industry. Fourth, I sort all industries based on *earnrank* and form two portfolios with top-2 industries being in one and bottom-2 industries being in the other. Fifth, I calculate monthly returns for the top-2 and bottom-2 portfolios. Finally, I calculate the difference between the top-2 and bottom-2 industry portfolios to obtain a measure of abnormal returns to earnings seasonalities. The calculations use quarterly earnings data and monthly stock return data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

Panel A: Summary statistics for returns on portfolios formed from individual stocks

Weight	Earnings rank	Avg. return (%)	St. dev. returns (%)	*t*-values	Sharpe ratio
VW	1 (Low)	1.45	5.50	5.69	0.20
VW	5 (High)	1.94	5.43	7.71	0.29
VW	5 - 1	0.49	4.37	2.42	0.11
EW	1 (Low)	1.76	5.29	7.20	0.26
EW	5 (High)	2.15	5.28	8.81	0.34
EW	5 - 1	0.39	2.65	3.17	0.15

Panel B: Summary statistics for returns on industry portfolios

Weight	Earnings rank	Avg. return (%)	St. dev. returns (%)	*t*-values	Sharpe ratio
VW	Bottom 2	1.39	6.39	4.71	0.16
VW	Top 2	1.79	6.07	6.39	0.23
VW	Top 2 - Bottom 2	0.40	6.98	1.24	0.06
EW	Bottom 2	1.66	6.56	5.48	0.20
EW	Top 2	2.08	6.09	7.37	0.28
EW	Top 2 - Bottom 2	0.42	5.83	1.55	0.07

Table 3: Earnings seasonalities and stock returns with controls

For individual stocks: First, I calculate the measure of predicted earnings seasonality, *earnrank*, in quarter q by ranking the 20 quarters of earnings data from the previous five years from largest to smallest and taking the average rank from the previous years of the same fiscal quarter earnings as the upcoming announcement. Second, I predict whether a firm will have an earnings announcement in month t by conditioning on a firm having an earnings announcement 12 months before. Third, I sort all the firms with predicted earnings announcement in month t to quintile portfolios with firms having the highest *earnrank* being in the top quintile portfolio (Q5) and firms having the lowest *earnrank* being in the bottom quintile portfolio (Q1). Fourth, I calculate monthly returns for the quintile portfolios. Fifth, I calculate the difference between the top and bottom quintile portfolio to obtain a measure of abnormal returns to earnings seasonalities. Finally, I regress returns of the quintile portfolios and the difference in their returns against the factors in Fama and French (1993) three-factor model and momentum. For industry portfolios: First, I calculate the predicted measure of earnings seasonality, *earnrank*, in quarter q for each stock. Second, I predict whether a firm will have an earnings announcement in month t by conditioning on a firm having an earnings announcement 12 months before. Third, I divide firms in industry portfolios based on 17 Fama-French industries and calculate the value-weighted average *earnrank* for each industry. Fourth, I sort all industries based on *earnrank* and form two portfolios with top-2 industries being in one and bottom-2 industries being in the other. Fifth, I calculate monthly returns for the top-2 and bottom-2 portfolios. Sixth, I calculate the difference between the top-2 and bottom-2 industry portfolios to obtain a measure of abnormal returns to earnings seasonalities. Finally, I regress returns of the top-2 and bottom-2 portfolios and the difference in their returns against the factors in Fama and French (1993) three-factor model and momentum. The calculations use quarterly earnings data and monthly stock return data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

Panel A: Four-factor regressions on returns of portfolios formed from individual stocks

Weight	Earnings rank	Four-factor α (%)	*t*-value
VW	1 (Low)	0.76	4.54
VW	5 (High)	1.29	6.94
VW	5 - 1	0.53	2.54
EW	1 (Low)	1.00	7.61
EW	5 (High)	1.43	10.52
EW	5 - 1	0.43	3.39

Panel B: Four-factor regressions on returns of industry portfolios

Weight	Earnings rank	Four-factor α (%)	*t*-value
VW	Bottom 2	0.62	2.55
VW	Top 2	1.19	4.95
VW	Top 2 - Bottom 2	0.57	1.70
EW	Bottom 2	0.87	3.68
EW	Top 2	1.42	6.45
EW	Top 2 - Bottom 2	0.55	1.95

5.1.3 Mutual exclusivity of cross-sectional return seasonalities and earnings seasonalities

To complete my baseline results, I combine these two seasonally recurring phenomena by regressing them against each other. Firstly, Panel A of Table 4 presents the average return alphas and beta coefficients from regressions that regress returns to cross-sectional seasonality portfolios against abnormal returns to earnings seasonalities in the same months. Results are strikingly similar to those presented before for return seasonality portfolios: Difference portfolios (same-month strategy – other-month strategy) formed from individual stocks exhibit an average monthly alpha of 1.96% (*t*-value = 6.75), which is almost equal to the average raw monthly return of 2.00% (*t*-value = 6.92) in Panel A of Table 1. Furthermore, the corresponding average monthly alpha for industry portfolios is 0.56% (*t*-value = 1.99), which is very close to the raw monthly return in Panel A of Table 1 averaging 0.57% (*t*-value = 2.01). In the case of both individual stocks and industry portfolios, the average coefficients for the effect of earnings seasonalities on return seasonalities are very low in magnitude and statistically insignificant.

Secondly, Panel B of Table 4 presents the results from regressions where the parts of return seasonalities and earnings seasonalities are reversed. Earnings seasonality difference portfolios formed from individual stocks exhibit an average value-weighted monthly alpha of 0.38% (*t*-value = 1.91) after controlling for return seasonalities in the same months.[13] This figure is slightly lower than the average raw earnings seasonality return of 0.49% (*t*-value = 2.42) presented in Panel A of Table 2. Moreover, the average slope coefficient for return seasonalities is highly statistically significant, yet rather small in magnitude, suggesting that these two phenomena share at least some underlying factors affecting the portfolio returns. Results for industry portfolios are similar, even though the effect of return seasonalities is even less pronounced: Difference industry portfolio earns an average monthly alpha of 0.36% (*t*-value = 1.13), which only slightly lower than the average raw monthly return of 0.40% (*t*-value = 1.24) presented in Panel B of Table 2.

[13] To make earnings seasonalities and return seasonalities comparable and to avoid the effect of external factors, return seasonalities used as right-hand side variables only include stocks with predicted earnings announcement in the given month.

To conclude on these baseline results combining cross-sectional return seasonalities and abnormal returns on earnings seasonalities: it appears that, despite the seeming similarity of these seasonality effects and the returns from investing in them (especially in the case of industry portfolios), they do not explain each other to any notable degree and stem mostly from different sources that remain at least partly unexplained.

Table 4: Mutual exclusivity of return seasonalities and earnings seasonalities

Results for both individual stocks and industry portfolios in Panel A are obtained by regressing returns to the same month strategy, the other-month strategy, and their difference in month *t* against earnings seasonality difference portfolio in the same month. Results for both individual stocks and industry portfolios in Panel B are obtained by regressing returns to the top portfolio, the bottom portfolio, and their difference in month *t* against return seasonality difference portfolio in the same month utilizing only firms with a predicted earnings announcement in the given month. The calculations use quarterly earnings data and monthly stock return data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

Panel A: Return seasonalities after controlling for earnings seasonalities

	Sort by											
	Same-month return				Other month return				Same - other			
Set of assets	α (%)	*t*-value	*b* (%)	*t*-value	α (%)	*t*-value	*b* (%)	*t*-value	α (%)	*t*-value	*b* (%)	*t*-value
Individual stocks	1.28	5.66	-2.45	-0.47	-0.68	-2.97	-10.32	-1.97	1.96	6.75	7.86	1.19
Industry portfolios	0.52	2.37	5.91	1.89	-0.04	-0.22	4.97	1.70	0.56	1.99	0.94	0.23

Panel B: Earnings seasonalities after controlling for return seasonalities

Set of assets	Earnings rank	α (%)	*t*-value	b (%)	*t*-value
Individual stocks	1 (Low)	1.58	7.73	-10.21	-4.15
	5 (High)	1.96	6.25	-1.73	-0.70
	5 - 1	0.38	1.91	8.48	4.35
Industry portfolios	Bottom 2	1.45	4.94	-8.34	-2.92
	Top 2	1.82	6.46	-3.47	-1.27
	Top 2 - Bottom 2	0.36	1.13	4.87	1.55

5.2 Return and earnings seasonalities after controlling for intra-industry overreaction

As mentioned in the introduction of this thesis, the objective of this study is to combine these two systematic seasonality effects and explain at least part of the prevalent and recurring occurrence of cross-sectional return seasonalities with behavioral biases stemming from judgmental heuristics first described by Tversky and Kahneman (1974). In the pursuit of this objective, I utilize the findings and methodology presented by Thomas and Zhang (2008) regarding investor overreaction to industry-specific news.

The methodology for accounting for intra-industry overreaction was explained in Section 4. To recap the basic methodology: I start by taking firm j and regressing historical monthly returns of the other firms operating in the same industry against monthly returns of firm j from the previous five years (see Equation (1)). After this, I take the average beta from these regressions to obtain a measure of historical prominence of firm j in its industry. The same procedure is then repeated by using each firm in turn as the right-hand side variable. For each of the 17 Fama-French industries, I define as industry leaders the firms which have the highest average betas from these regressions against historical returns of other firms in the same industry.

As the prominence of a firm within its industry is subject to change, I re-run the aforementioned regressions every five years to obtain new industry leaders for the next five-year period. Due to this procedure, industry leaders are required to have non-missing return data also for this five-year period in addition to the historical five-year period.

To isolate the effect of intra-industry overreaction to industry leaders' earnings announcements, I divide monthly return coefficient of each firm with each firm's own daily return coefficient on the industry leaders' earnings announcement date (see Equation (2)). Throughout this section, I will present results that have been calculated using one-day returns and top-3 leaders for each industry.[14] Thus, in each month, the effect of maximum of three trading days are isolated for each firm.

The structure of this section follows that of the previous section where baseline results were discussed. I will first present the intra-industry overreaction adjusted results for cross-sectional return seasonalities. After that I will discuss adjusted earnings seasonality returns. Finally, I will combine the adjusted results for these two phenomena and present the main findings of this study.

5.2.1 Cross-sectional seasonalities in individual stock and industry portfolio returns

Table 5 presents the intra-industry overreaction adjusted results for seasonalities in the cross section of individual stocks and industry portfolios. The analyses used to obtain these results are equivalent to those used for Table 1 in the previous section. Panel A of Table 5 presents the summary statistics for returns excluding daily returns on three industry leaders' earnings announcement dates. These results are obtained using the original sets of individual stocks and industry portfolios in each month. In other words, decile portfolios as well as the top and the bottom industry portfolios are formed based on unadjusted average same-month and other-month returns. Panel B of Table 5 presents the results using updated sets of individual stocks and industry portfolios in each month. To obtain these results, decile portfolios as well as the top and the bottom industry portfolios are formed based on intra-industry overreaction adjusted average same-month and other-month returns. These two different sets of analyses were conducted to account for potential change in some months' portfolio composition after adjustment for intra-industry overreaction.

In both Panel A and B of Table 5, the results for return seasonalities after adjustment for intra-industry overreaction are similar, yet slightly less pronounced than raw return seasonalities presented in Table 1. Using the original sets of individual stocks, monthly

[14] The same analyses have been conducted using two alternative specifications: firstly, using one-day returns and one industry leader, and secondly, using three-day ($t-1$ through $t+1$) cumulative returns and one industry leader. The latter of these specifications is based on DellaVigna and Pollet (2009) who find that reactions to earnings announcement may be delayed if they are released on Friday. Results using these specifications are presented in the Appendices. In almost of all the cases, they are materially similar to those using one-day returns and three industry leaders.

returns for the difference portfolio average at 1.65% (t-value = 5.06), while the average monthly four-factor alpha equals 1.61% (t-value = 5.48). Using the updated sets of individual stocks, average monthly return for the difference portfolios equals 1.82% (t-value = 4.20), whereas monthly four-factor alpha averages at 1.75% (t-value = 4.72). [15] Return seasonalities for individual stocks therefore seem to remain almost as strong when controlling for intra-industry overreaction.

Results for industry portfolios in Table 5 are more interesting: Using the original sets of industry portfolios, monthly returns for the difference portfolio average at 0.45% (t-value = 1.55). However, the average four-factor alpha for this set of assets equals only 0.25% (t-value = 0.83). The results using the updated sets of industry portfolios are highly similar to these, as average monthly return for the difference portfolio equals 0.55% (t-value = 1.66) and monthly four-factor alpha averages at 0.30% (t-value = 0.93%). These results suggest that even though return seasonalities do not fully disappear when adjusted returns are used, intra-industry overreaction may be a partial explanation for seasonalities within the cross section of industry portfolios. However, the results for industry portfolios using the two alternative specifications (presented in Appendices 3 and 4) are rather different from the results presented here: in both of these cases, the average monthly returns and four-factor alphas remain statistically significant. Thus, further analyses using different intra-industry overreaction adjustment methods are needed in the future to shed more light on this interesting phenomenon.

[15] Appendices 3 and 4 present the results from the same analyses using one-day returns and one industry leader, and three-day returns and one industry leader, respectively. The results for individual stocks are highly similar to those presented in Table 5.

Table 5: Return seasonalities in individual stocks and industry-sorted portfolios excluding daily returns on three industry leaders' earnings announcement dates

For individual stocks: First, I calculate monthly returns adjusted for intra-industry overreaction by excluding the one-day returns from dates when each industry's top-3 leaders had their earnings announcements. Second, I calculate the 20-year average same-calendar month and other-calendar month returns for each stock in the sample. Third, in each monthly cross section, I divide firms in ten decile portfolios based on their average same-month and other-month returns. Fourth, I calculate the return on the same-month and other-month strategy: Same-month strategy takes a long position in the top decile portfolio and a short position in the bottom decile portfolio based on the 20-year average same-month return. Other-month strategy takes a long position in the top decile portfolio and a short position in the bottom decile portfolio based on the 20-year average same-month return. Finally, I calculate the difference between the same-month strategy and other-month strategy. For industry portfolios: First, I divide firms to industry portfolios based on 17 Fama-French industries. Second, I calculate value-weighted monthly return adjusted for intra-industry overreaction by excluding the one-day returns from dates when each industry's top-3 leaders had their earnings announcements for each industry portfolio in each monthly cross section. Third, I calculate the return on the same-month and other-month strategy: Same-month strategy takes a long position in the top-2 industry portfolios and a short position in the bottom-2 industry based on their 20-year average same-calendar month return. Other-month strategy takes a long position in the top-2 industry portfolios and a short position in the bottom-2 industry portfolios based on their 20-year average other-calendar month return. Finally, as in the case of portfolios formed from individual stocks, I calculate the difference between the same-month strategy and other-month strategy to capture the cross-sectional seasonality effect. To obtain four-factor alphas, I regress the returns of the same-month and other-month strategy as well as their difference against the factors in Fama and French (1993) three-factor model and momentum. The calculations use quarterly earnings data as well as monthly and daily stock return data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

Panel A: Summary statistics for returns excluding industry leaders' earnings announcement dates using original set of individual stocks and industry portfolios (formed based on unadjusted same-month and other-month average returns)

	Monthly returns and alphas (%) Sort by						*t*-values Sort by					
Set of	Same-month		Other-month		Same-other		Same-month		Other-month		Same-other	
assets	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α
Individual stocks	1.12	1.23	-0.53	-0.38	1.65	1.61	5.06	5.48	-2.38	-2.35	5.58	5.76
Industry portfolios	0.42	0.37	-0.03	0.12	0.45	0.25	1.89	1.62	-0.14	0.65	1.55	0.83

Panel B: Summary statistics for returns excluding industry leaders' earnings announcement dates using updated set of individual stocks and industry portfolios (formed based on same-month and other-month average returns calculated from monthly returns adjusted for industry leaders' earnings announcement dates)

	Monthly returns and alphas (%) Sort by						*t*-values Sort by					
Set of	Same-month		Other-month		Same-other		Same-month		Other-month		Same-other	
assets	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α
Individual stocks	0.93	1.04	-0.89	-0.71	1.82	1.75	4.20	4.72	-4.04	-4.28	6.34	6.51
Industry portfolios	0.38	0.36	-0.17	0.05	0.55	0.30	1.67	1.52	-0.70	0.25	1.66	0.93

5.2.2 Abnormal returns to earnings seasonalities in individual stocks and industry portfolios

Table 6 continues by presenting the intra-industry overreaction adjusted returns to earnings seasonality portfolios. Panel A of Table 6 shows the summary statistics for returns on portfolios formed from individual stocks after adjusting for each firm's own return on industry leaders' earnings announcement dates. Panel B of Table 6 shows the same summary statistics for returns on industry portfolios. Overall, the results are highly comparable to the raw returns presented in Table 2: Value-weighted difference portfolio of individual stocks earns an average monthly return of 0.47% (t-value = 2.35), whereas value-weighted industry difference portfolios earns on average a monthly return of 0.46% (t-value = 1.40).[16] For both individual stocks and industry portfolios, equal-weighted results are slightly smaller in magnitude yet stronger in statistical significance.

[16] Appendices 5 and 6 present the results from the same analyses using one-day returns and one industry leader, and three-day returns and one industry leader, respectively. The results for both individual stocks and industry portfolios are highly similar to those presented in Table 6.

Table 6: Earnings seasonalities and stock returns excluding daily returns on three industry leaders' earnings announcement dates

For individual stocks: First, I calculate the measure of predicted earnings seasonality, *earnrank*, in quarter q by ranking the 20 quarters of earnings data from the previous five years from largest to smallest and taking the average rank from the previous years of the same fiscal quarter earnings as the upcoming announcement. Second, I predict whether a firm will have an earnings announcement in month t by conditioning on a firm having an earnings announcement 12 months before. Third, I sort all the firms with predicted earnings announcement in month t to quintile portfolios with firms having the highest *earnrank* being in the top quintile portfolio (Q5) and firms having the lowest *earnrank* being in the bottom quintile portfolio (Q1). Fourth, I calculate monthly returns adjusted for intra-industry overreaction for each stock in the sample by excluding the one-day returns from dates when each industry's top-3 leaders had their earnings announcements. Fifth, I calculate monthly returns for the quintile portfolios. Finally, I calculate the difference between the top and bottom quintile portfolio to obtain a measure of abnormal returns to earnings seasonalities. For industry portfolios: First, I calculate the predicted measure of earnings seasonality, *earnrank*, in quarter q for each stock. Second, I predict whether a firm will have an earnings announcement in month t by conditioning on a firm having an earnings announcement 12 months before. Third, I divide firms in industry portfolios based on 17 Fama-French industries and calculate the value-weighted average *earnrank* for each industry. Fourth, I sort all industries based on *earnrank* and form two portfolios with top-2 industries being in one and bottom-2 industries being in the other. Fifth, I calculate monthly returns adjusted for intra-industry overreaction for the top-2 and bottom-2 portfolios by excluding the one-day returns from dates when each industry's top-3 leaders had their earnings announcements. Finally, I calculate the difference between the top-2 and bottom-2 industry portfolios to obtain a measure of abnormal returns to earnings seasonalities. The calculations use quarterly earnings data as well as monthly and daily stock return data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

Panel A: Summary statistics for returns on portfolios formed from individual stocks excluding industry leaders' earnings announcement date returns

Weight	Earnings rank	Avg. return (%)	St. dev. returns (%)	*t*-values	Sharpe ratio
VW	1 (Low)	1.31	5.36	5.29	0.18
VW	5 (High)	1.78	5.29	7.28	0.27
VW	5 - 1	0.47	4.34	2.35	0.11
EW	1 (Low)	1.69	5.10	7.18	0.26
EW	5 (High)	2.03	5.08	8.65	0.33
EW	5 - 1	0.34	2.69	2.73	0.13

Panel B: Summary statistics for returns on industry portfolios excluding industry leaders' earnings announcement date returns

Weight	Earnings rank	Avg. return (%)	St. dev. returns (%)	*t*-values	Sharpe ratio
VW	Bottom 2	1.31	6.23	4.55	0.15
VW	Top 2	1.77	5.96	6.41	0.23
VW	Top 2 - Bottom 2	0.46	7.03	1.40	0.06
EW	Bottom 2	1.61	6.27	5.56	0.20
EW	Top 2	2.06	5.95	7.49	0.28
EW	Top 2 - Bottom 2	0.45	5.78	1.68	0.08

Table 7 completes the results for abnormal returns to earnings seasonalities after adjustment for intra-industry overreaction by presenting the monthly alphas after controlling for the factors in Fama and French (1993) three-factor model and momentum. The main results remain almost unchanged[17] compared to the unadjusted alphas presented in Table 3: As Panel A of Table 7 shows, value-weighted difference portfolio formed from individual stocks exhibits an average monthly four-factor alpha of 0.52% (*t*-value = 2.50), which is slightly stronger than the average adjusted, uncontrolled monthly return presented in the previous table. Similarly, the average monthly four-factor alpha for value-weighted industry difference portfolios equals 0.57% (*t*-value = 1.69), thus slightly exceeding the average of adjusted and uncontrolled monthly returns shown in the previous table. Again, equal-weighted results for both individual stocks and industry portfolios are slightly lower in magnitude but more statistically significant.

To conclude on the adjusted results for abnormal returns to earnings seasonalities: It appears that intra-industry overreaction does not play any significant role in explaining abnormal returns to earnings seasonalities for either individual stocks or industry portfolios. However, my main hypotheses does not make any predictions regarding this, and the analyses used to obtain these results were mainly conducted to keep the results for cross-sectional return seasonalities and abnormal returns to earnings seasonalities comparable.

[17] The same applies to the results from the same analyses using one-day returns and one industry leader, and three-day returns and one industry leader presented in Appendices 7 and 8, respectively.

Table 7: Earnings seasonalities and stock returns with controls excluding daily returns on three industry leaders' earnings announcement dates

For individual stocks: First, I calculate the measure of predicted earnings seasonality, *earnrank*, in quarter q by ranking the 20 quarters of earnings data from the previous five years from largest to smallest and taking the average rank from the previous years of the same fiscal quarter earnings as the upcoming announcement. Second, I predict whether a firm will have an earnings announcement in month t by conditioning on a firm having an earnings announcement 12 months before. Third, I sort all the firms with predicted earnings announcement in month t to quintile portfolios with firms having the highest *earnrank* being in the top quintile portfolio (Q5) and firms having the lowest *earnrank* being in the bottom quintile portfolio (Q1). Fourth, I calculate monthly returns adjusted for intra-industry overreaction for each stock in the sample by excluding the one-day returns from dates when each industry's top-3 leaders had their earnings announcements. Fifth, I calculate monthly returns for the quintile portfolios. Sixth, I calculate the difference between the top and bottom quintile portfolio to obtain a measure of abnormal returns to earnings seasonalities. Finally, I regress returns of the quintile portfolios and the difference in their returns against the factors in Fama and French (1993) three-factor model and momentum. For industry portfolios: First, I calculate the predicted measure of earnings seasonality, *earnrank*, in quarter q for each stock. Second, I predict whether a firm will have an earnings announcement in month t by conditioning on a firm having an earnings announcement 12 months before. Third, I divide firms in industry portfolios based on 17 Fama-French industries and calculate the value-weighted average *earnrank* for each industry. Fourth, I sort all industries based on *earnrank* and form two portfolios with top-2 industries being in one and bottom-2 industries being in the other. Fifth, I calculate monthly returns adjusted for intra-industry overreaction for the top-2 and bottom-2 portfolios by excluding the one-day returns from dates when each industry's top-3 leaders had their earnings announcements. Sixth, I calculate the difference between the top-2 and bottom-2 industry portfolios to obtain a measure of abnormal returns to earnings seasonalities. Finally, I regress returns of the top-2 and bottom-2 portfolios and the difference in their returns against the factors in Fama and French (1993) three-factor model and momentum. The calculations use quarterly earnings data as well as monthly and daily stock return data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

Panel A: Four-factor regressions on returns of portfolios formed from individual stocks excluding industry leaders' earnings announcement date returns

Weight	Earnings rank	Four-factor α (%)	*t*-value
VW	1 (Low)	0.64	3.92
VW	5 (High)	1.16	6.24
VW	5 - 1	0.52	2.50
EW	1 (Low)	0.97	7.20
EW	5 (High)	1.36	10.01
EW	5 - 1	0.38	2.96

Panel B: Four-factor regressions on returns of industry portfolios excluding industry leaders' earnings announcement date returns

Weight	Earnings rank	Four-factor α (%)	*t*-value
VW	Bottom 2	0.60	2.43
VW	Top 2	1.17	4.94
VW	Top 2 - Bottom 2	0.57	1.69
EW	Bottom 2	0.87	3.73
EW	Top 2	1.42	6.62
EW	Top 2 - Bottom 2	0.55	1.98

5.2.3 Mutual exclusivity of cross-sectional return seasonalities and earnings seasonalities after controlling for intra-industry overreaction

This section brings together the three main phenomena discussed in this paper by presenting the results from combining cross-sectional return seasonalities, abnormal returns to earnings seasonalities and intra-industry overreaction to earnings announcements. Therefore, this section presents the results for testing my second main hypotheses, whereby I predicted that cross-sectional return seasonalities in industry portfolios are explained by the joint effect of positive correlation in intra-industry earnings seasonalities and investor overreaction to industry-specific earnings announcement information.

Panel A of Table 8[18] presents the average return alphas and beta coefficients for regressions that regress intra-industry overreaction adjusted returns to cross-sectional seasonality portfolios against correspondingly adjusted abnormal returns to earnings seasonality in the same months.[19] At first glance, the results look rather disappointing: Firstly, returns to seasonality difference portfolios formed from individual stocks remain highly positive and exhibit an average monthly alpha of 1.77% (t-value = 6.13). The average alpha is slightly lower than the average of 1.96% (t-value = 6.75) for unadjusted returns presented in Table 4. Secondly, also returns to seasonality difference portfolios formed from industry portfolios continue to earn positive returns and exhibit a monthly alpha of 0.51% (t-value = 1.55). Again, the average alpha is slightly lower than the monthly average of 0.56% (t-value = 1.99) for unadjusted returns presented in Table 4.

However, what makes the aforementioned results interesting is the average beta coefficient from the regressions that use adjusted returns for industry portfolios: Whereas the average beta from regressions using unadjusted returns for industry portfolios is indistinguishable

[18] Panel B of Table 8 presents the results from regressions where the parts of returns seasonalities and earnings seasonalities are reversed. These results are not the main area of interest in study and they remain almost unchanged compared to the equivalent results presented in Table 4. The results from the same analyses using one-day returns and one industry leader, and three-day returns and one industry leader are presented in Panel B of Appendices 9 and 10, respectively.

[19] Panel A of Appendices 9 and 10 present the results from the same analyses using one-day returns and one industry leader, and three-day returns and one industry leader, respectively. Most of the results are similar to those presented here, but the magnitude of beta coefficients is lower using these alternative specifications for measuring intra-industry overreaction.

from zero (beta = 0.94% and *t*-value = 0.23), the equivalent figures for regressions using intra-industry overreaction adjusted returns for industry portfolios are materially higher in magnitude and marginally significant (beta = 8.01% and *t*-value = 1.71). These results suggest that, even though the joint effect of abnormal returns to earnings seasonalities and intra-industry overreaction to earnings announcement information to cross-sectional return seasonalities in industry portfolios is rather limited in magnitude, it appears to have at least some explanatory power in dismantling this cross-sectional seasonality effect. Implications of these results are discussed in more detail in the next section.

Table 8: Mutual exclusivity of cross-sectional return seasonalities and earnings seasonalities excluding daily returns on three industry leaders' earnings announcement dates

Results for both individual stocks and industry portfolios in Panel A are obtained by regressing the intra-industry overreaction adjusted returns (one-day return, three industry leaders) to the same month strategy, the other-month strategy, and their difference in month *t* against earnings seasonality difference portfolio in the same month. Results for both individual stocks and industry portfolios in Panel B are obtained by regressing the intra-industry overreaction adjusted returns (one-day return, one industry leader) to the top portfolio, the bottom portfolio, and their difference in month *t* against return seasonality difference portfolio in the same month utilizing only firms with a predicted earnings announcement in the given month. The calculations use quarterly earnings data as well as monthly and daily stock return data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

Panel A: Return seasonalities after controlling for earnings seasonalities and industry leaders' earnings announcement date returns (same-month and other-month average returns calculated from monthly returns adjusted for industry leaders' earnings announcement date returns)

	Sort by											
	Same-month return				Other month return				Same - other			
Set of assets	α (%)	*t* -value	*b* *(%)*	*t* -value	α (%)	*t* -value	*b* *(%)*	*t* -value	α (%)	*t* -value	*b* *(%)*	*t* -value
Individual stocks	0.94	4.24	-2.99	-0.59	-0.82	-3.73	-14.39	-2.84	1.77	6.13	11.39	1.73
Industry portfolios	0.35	1.56	5.62	1.74	-0.16	-0.66	-2.38	-0.70	0.51	1.55	8.01	1.71

Panel B: Earnings seasonalities after controlling for return seasonalities and industry leaders' earnings announcement date returns (same-month and other-month average returns calculated from monthly returns adjusted for industry leaders' earnings announcement date returns)

Set of assets	Earnings rank	α (%)	*t* -value	b (%)	*t* -value
Individual stocks	1 (Low)	1.40	5.66	-7.80	-3.19
	5 (High)	1.78	7.20	0.62	0.26
	5 - 1	0.38	1.92	8.43	4.29
Industry portfolios	Bottom 2	1.37	4.76	-8.00	-2.81
	Top 2	1.77	6.41	-0.91	-0.33
	Top 2 - Bottom 2	0.41	1.26	7.08	2.20

6. Discussion and conclusions

Recent asset pricing literature has documented seasonally recurring phenomena leading to strongly positive and persistent abnormal returns. For my study, the most relevant of these findings are those of Keloharju, Linnainmaa, and Nyberg (2016) regarding return seasonalities in the cross section of individual stocks and industry portfolios, as well as those of Chang et al. (2017) regarding abnormal returns to earnings seasonalities.

The objective of my study was to explain at least part of the prevalent and recurring occurrence of return seasonalities, especially in the cross section of industry portfolios, by a combination of abnormal returns to earnings seasonalities and behavioral biases stemming from judgmental heuristics described by Tversky and Kahneman (1974). To achieve this objective in practice, I based my methodology on the findings and methods of Thomas and Zhang (2008) regarding investor overreaction to intra-industry earnings announcement news.

Despite the strong theoretical foundation as well as promising baseline results, the main results of this thesis are inconclusive: Regarding my first main hypothesis, I find that portfolios formed based on industry classification earn positive abnormal returns to earnings seasonalities, even though the results are only marginally significant. Regarding my second main hypothesis – which is the most important one of this thesis – I find that cross-sectional return seasonalities in industry portfolios are lower in magnitude when the effect of intra-industry overreaction to earnings seasonalities is accounted for. Even though this effect is limited – the average monthly return coefficient of 0.57% (t-value = 2.01) for the industry difference portfolio decreases to an average alpha of 0.51% (t-value = 1.55) – there are certain indications for the importance of intra-industry overreaction in explaining seasonalities in the cross section of industry portfolios. Firstly, the average four-factor alpha for return seasonalities in industry portfolios decreases significantly after adjusting returns for intra-industry overreaction to earnings announcements. Secondly, in regressing return seasonalities against earnings seasonalities using intra-industry overreaction adjusted returns, the average beta coefficient for earnings seasonalities in industry portfolios is materially strengthened compared to that using unadjusted returns.

This study is the first attempt to combine return and earnings seasonality effects using a behavioral framework of intra-industry investor overreaction. Despite providing only inconclusive evidence and marginally significant results on relations between these three phenomena, it contributes to the existing literature by structuring the theoretical reasoning behind this potential explanation as well as by presenting the basic methodology for further testing my main hypotheses. In conclusion, intra-industry overreaction to seasonally recurring firm-events, such as earnings announcements, potentially provides at least a partial explanation for pervasive and persistent cross-sectional return seasonalities. However, further research utilizing enhanced methods is needed to shed more light on this explanation.

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Appendices

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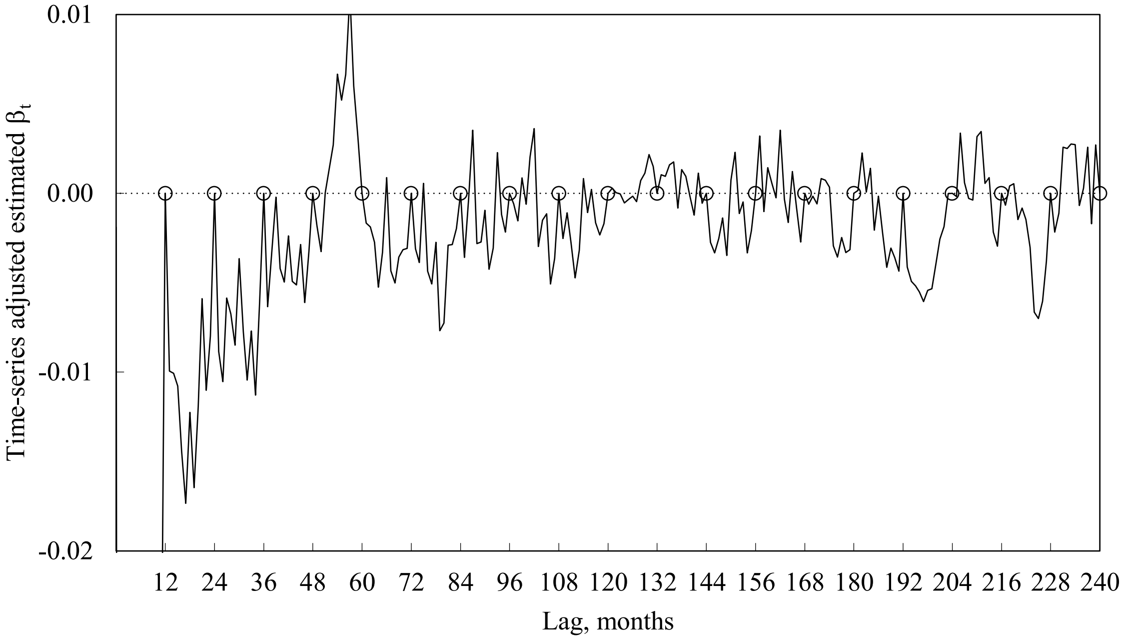
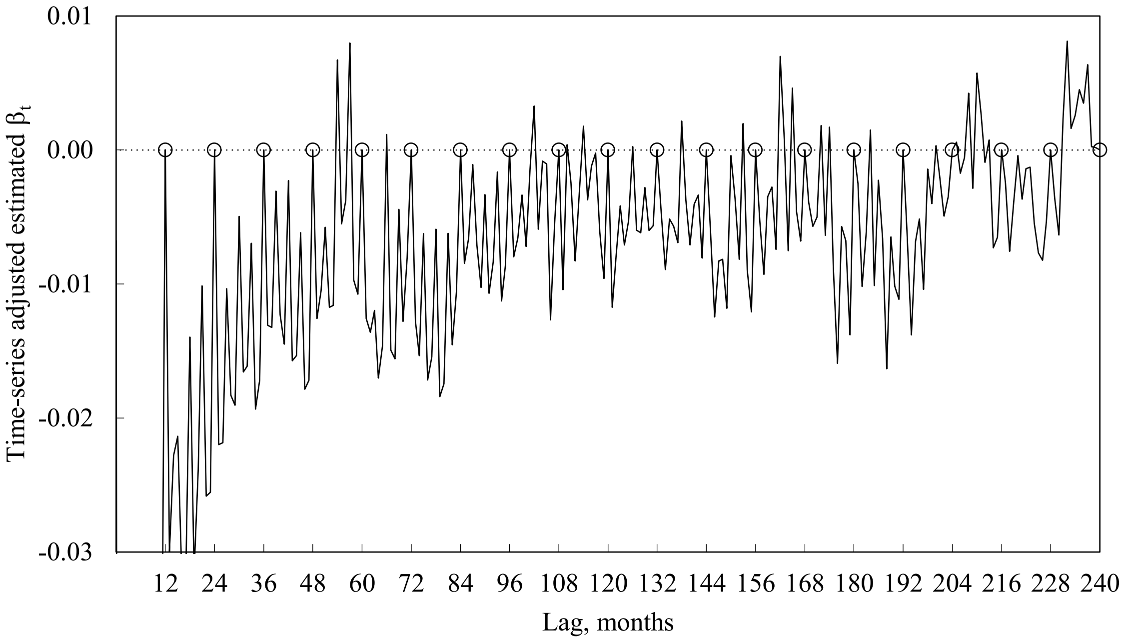


Appendix 1: Seasonalities in volumes of individual stocks

This figure plots exponential drift-adjusted slope coefficients from univariate Fama and MacBeth (1973) regressions of t volumes against month $t - k$ volumes, $v_{i,t} = a_t + b_t v_{i,t-k} + e_{i,t}$, with k ranging from 1 to 240 months. Estimates at annual lags (denoted by the circles) have been adjusted to be zero after correcting for downward-trending exponential drift in slope coefficients. Consequently, any month with negative coefficient has less exponential drift-adjusted predictive power on volume in month t. The regressions use monthly volume data from January 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.



Appendix 2: Seasonalities in volumes of individual stocks excluding earnings announcement and dividend distributions months

This figure plots exponential drift-adjusted slope coefficients from univariate Fama and MacBeth (1973) regressions of *t* volumes against month $t - k$ volumes, $v_{i,t} = a_t + b_t v_{i,t\text{-}k} + e_{i,t}$, with *k* ranging from 1 to 240 months. Estimates at annual lags (denoted by the circles) have been adjusted to be zero after correcting for downward-trending exponential drift in slope coefficients. Consequently, any month with negative coefficient has less exponential drift-adjusted predictive power on volume in month *t.* Methodology used to calculate the slope coefficients is equivalent to that of Figure [X], but the sample excludes firms with earnings announcement or dividend distribution in month *t.* The circles denote estimates at annual lags. The regressions use monthly volume data from January 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

Appendix 3: Return seasonalities in individual stocks and industry sorted portfolios excluding daily returns on one industry leader's earnings announcement dates

For individual stocks: First, I calculate monthly returns adjusted for intra-industry overreaction by excluding the one-day returns from dates when each industry's leader had their earnings announcements. Second, I calculate the 20-year average same-calendar month and other-calendar month returns for each stock in the sample. Third, in each monthly cross section, I divide firms in ten decile portfolios based on their average same-month and other-month returns. Fourth, I calculate the return on the same-month and other-month strategy: Same-month strategy takes a long position in the top decile portfolio and a short position in the bottom decile portfolio based on the 20-year average same-month return. Other-month strategy takes a long position in the top decile portfolio and a short position in the bottom decile portfolio based on the 20-year average same-month return. Finally, I calculate the difference between the same-month strategy and other-month strategy. For industry portfolios: First, I divide firms to industry portfolios based on 17 Fama-French industries. Second, I calculate value-weighted monthly return adjusted for intra-industry overreaction by excluding the one-day returns from dates when each industry's top-3 leaders had their earnings announcements for each industry portfolio in each monthly cross section. Third, I calculate the return on the same-month and other-month strategy: Same-month strategy takes a long position in the top-2 industry portfolios and a short position in the bottom-2 industry based on their 20-year average same-calendar month return. Other-month strategy takes a long position in the top-2 industry portfolios and a short position in the bottom-2 industry portfolios based on their 20-year average other-calendar month return. Finally, as in the case of portfolios formed from individual stocks, I calculate the difference between the same-month strategy and other-month strategy to capture the cross-sectional seasonality effect. To obtain four-factor alphas, I regress the returns of the same-month and other-month strategy as well as their difference against the factors in Fama and French (1993) three-factor model and momentum. The calculations use quarterly earnings data as well as monthly and daily stock return data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

Panel A: Summary statistics for returns excluding industry leaders' earnings announcement dates using original set of individual stocks and industry portfolios (formed based on unadjusted same-month and other-month average returns)

	Monthly returns and alphas (%) Sort by						*t*-values Sort by					
Set of	Same-month		Other-month		Same-other		Same-month		Other-month		Same-other	
assets	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α
Individual stocks	1.18	1.31	-0.52	-0.37	1.69	1.68	5.14	5.70	-2.27	-2.24	5.58	5.90
Industry portfolios	0.60	0.58	-0.09	-0.03	0.69	0.61	2.70	2.58	-0.43	-0.15	2.44	2.12

Panel B: Summary statistics for returns excluding industry leaders' earnings announcement dates using updated set of individual stocks and industry portfolios (formed based on same-month and other-month average returns calculated from monthly returns adjusted for industry leaders' earnings announcement dates)

	Monthly returns and alphas (%) Sort by						*t*-values Sort by					
Set of	Same-month		Other-month		Same-other		Same-month		Other-month		Same-other	
assets	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α
Individual stocks	0.92	1.05	-1.02	-0.83	1.94	1.88	4.06	4.59	-4.60	-5.07	6.64	6.86
Industry portfolios	0.57	0.59	-0.25	-0.17	0.82	0.76	2.49	2.51	-1.06	-0.79	2.49	2.27

Appendix 4: Return seasonalities in individual stocks and industry-sorted portfolios excluding cumulative three-day returns on one industry leader's earnings announcement dates

For individual stocks: First, I calculate monthly returns adjusted for intra-industry overreaction by excluding the three-day returns from dates when each industry's leader had their earnings announcements. Second, I calculate the 20-year average same-calendar month and other-calendar month returns for each stock in the sample. Third, in each monthly cross section, I divide firms in ten decile portfolios based on their average same-month and other-month returns. Fourth, I calculate the return on the same-month and other-month strategy: Same-month strategy takes a long position in the top decile portfolio and a short position in the bottom decile portfolio based on the 20-year average same-month return. Other-month strategy takes a long position in the top decile portfolio and a short position in the bottom decile portfolio based on the 20-year average same-month return. Finally, I calculate the difference between the same-month strategy and other-month strategy. For industry portfolios: First, I divide firms to industry portfolios based on 17 Fama-French industries. Second, I calculate value-weighted monthly return adjusted for intra-industry overreaction by excluding the one-day returns from dates when each industry's top-3 leaders had their earnings announcements for each industry portfolio in each monthly cross section. Third, I calculate the return on the same-month and other-month strategy: Same-month strategy takes a long position in the top-2 industry portfolios and a short position in the bottom-2 industry based on their 20-year average same-calendar month return. Other-month strategy takes a long position in the top-2 industry portfolios and a short position in the bottom-2 industry portfolios based on their 20-year average other-calendar month return. Finally, as in the case of portfolios formed from individual stocks, I calculate the difference between the same-month strategy and other-month strategy to capture the cross-sectional seasonality effect. To obtain four-factor alphas, I regress the returns of the same-month and other-month strategy as well as their difference against the factors in Fama and French (1993) three-factor model and momentum. The calculations use quarterly earnings data as well as monthly and daily stock return data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

Panel A: Summary statistics for returns excluding industry leaders' earnings announcement dates using original set of individual stocks and industry portfolios (formed based on unadjusted same-month and other-month average returns)

	Monthly returns and alphas (%) Sort by						*t*-values Sort by					
Set of	Same-month		Other-month		Same-other		Same-month		Other-month		Same-other	
assets	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α
Individual stocks	1.12	1.22	-0.51	-0.40	1.63	1.62	5.03	5.42	-2.26	-2.47	5.55	5.90
Industry portfolios	0.58	0.57	-0.09	-0.06	0.67	0.63	2.65	2.52	-0.43	-0.31	2.44	2.23

Panel B: Summary statistics for returns excluding industry leaders' earnings announcement dates using updated set of individual stocks and industry portfolios (formed based on same-month and other-month average returns calculated from monthly returns adjusted for industry leaders' earnings announcement dates)

	Monthly returns and alphas (%) Sort by						*t*-values Sort by					
Set of	Same-month		Other-month		Same-other		Same-month		Other-month		Same-other	
assets	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α	Avg	4F α
Individual stocks	0.87	0.94	-0.84	-0.71	1.71	1.65	3.86	4.11	-3.89	-4.51	6.11	6.28
Industry portfolios	0.42	0.43	-0.21	-0.13	0.63	0.55	1.97	1.97	-0.96	-0.65	2.19	1.91

Appendix 5: Earnings seasonalities and stock returns excluding daily returns on one industry leader's earnings announcement dates

For individual stocks: First, I calculate the measure of predicted earnings seasonality, *earnrank*, in quarter q by ranking the 20 quarters of earnings data from the previous five years from largest to smallest and taking the average rank from the previous years of the same fiscal quarter earnings as the upcoming announcement. Second, I predict whether a firm will have an earnings announcement in month t by conditioning on a firm having an earnings announcement 12 months before. Third, I sort all the firms with predicted earnings announcement in month t to quintile portfolios with firms having the highest *earnrank* being in the top quintile portfolio (Q5) and firms having the lowest *earnrank* being in the bottom quintile portfolio (Q1). Fourth, I calculate monthly returns adjusted for intra-industry overreaction for each stock in the sample by excluding the one-day returns from dates when each industry's leader had their earnings announcements. Fifth, I calculate monthly returns for the quintile portfolios. Finally, I calculate the difference between the top and bottom quintile portfolio to obtain a measure of abnormal returns to earnings seasonalities. For industry portfolios: First, I calculate the predicted measure of earnings seasonality, *earnrank*, in quarter q for each stock. Second, I predict whether a firm will have an earnings announcement in month t by conditioning on a firm having an earnings announcement 12 months before. Third, I divide firms in industry portfolios based on 17 Fama-French industries and calculate the value-weighted average *earnrank* for each industry. Fourth, I sort all industries based on *earnrank* and form two portfolios with top-2 industries being in one and bottom-2 industries being in the other. Fifth, I calculate monthly returns adjusted for intra-industry overreaction for the top-2 and bottom-2 portfolios by excluding the one-day returns from dates when each industry's leader had their earnings announcements. Finally, I calculate the difference between the top-2 and bottom-2 industry portfolios to obtain a measure of abnormal returns to earnings seasonalities. The calculations use quarterly earnings data as well as monthly and daily stock return data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

Panel A: Summary statistics for returns on portfolios formed from individual stocks excluding industry leaders' earnings announcement date returns

Weight	Earnings rank	Avg. return (%)	St. dev. returns (%)	*t*-values	Sharpe ratio
VW	1 (Low)	1.39	5.45	5.51	0.19
VW	5 (High)	1.87	5.35	7.57	0.28
VW	5 - 1	0.48	4.35	2.40	0.11
EW	1 (Low)	1.75	5.22	7.24	0.26
EW	5 (High)	2.09	5.18	8.71	0.33
EW	5 - 1	0.34	2.68	2.73	0.13

Panel B: Summary statistics for returns on industry portfolios excluding industry leaders' earnings announcement date returns

Weight	Earnings rank	Avg. return (%)	St. dev. returns (%)	*t*-values	Sharpe ratio
VW	Bottom 2	1.37	6.33	4.66	0.16
VW	Top 2	1.79	5.98	6.48	0.24
VW	Top 2 - Bottom 2	0.43	7.02	1.32	0.06
EW	Bottom 2	1.63	6.46	5.46	0.20
EW	Top 2	2.07	6.01	7.42	0.28
EW	Top 2 - Bottom 2	0.43	5.79	1.61	0.07

Appendix 6: Earnings seasonalities and stock returns excluding cumulative three-day returns on one industry leader's earnings announcement dates

For individual stocks: First, I calculate the measure of predicted earnings seasonality, *earnrank*, in quarter q by ranking the 20 quarters of earnings data from the previous five years from largest to smallest and taking the average rank from the previous years of the same fiscal quarter earnings as the upcoming announcement. Second, I predict whether a firm will have an earnings announcement in month t by conditioning on a firm having an earnings announcement 12 months before. Third, I sort all the firms with predicted earnings announcement in month t to quintile portfolios with firms having the highest *earnrank* being in the top quintile portfolio (Q5) and firms having the lowest *earnrank* being in the bottom quintile portfolio (Q1). Fourth, I calculate monthly returns adjusted for intra-industry overreaction for each stock in the sample by excluding the three-day (t – 1 through t + 1) returns from dates when each industry's leader had their earnings announcements. Fifth, I calculate monthly returns for the quintile portfolios. Finally, I calculate the difference between the top and bottom quintile portfolio to obtain a measure of abnormal returns to earnings seasonalities. For industry portfolios: First, I calculate the predicted measure of earnings seasonality, *earnrank*, in quarter q for each stock. Second, I predict whether a firm will have an earnings announcement in month t by conditioning on a firm having an earnings announcement 12 months before. Third, I divide firms in industry portfolios based on 17 Fama-French industries and calculate the value-weighted average *earnrank* for each industry. Fourth, I sort all industries based on *earnrank* and form two portfolios with top-2 industries being in one and bottom-2 industries being in the other. Fifth, I calculate monthly returns adjusted for intra-industry overreaction for the top-2 and bottom-2 portfolios by excluding the three-day (t – 1 through t + 1) returns from dates when each industry's leader had their earnings announcements. Finally, I calculate the difference between the top-2 and bottom-2 industry portfolios to obtain a measure of abnormal returns to earnings seasonalities. The calculations use quarterly earnings data as well as monthly and daily stock return data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

Panel A: Summary statistics for returns on portfolios formed from individual stocks excluding industry leaders' earnings announcement date returns

Weight	Earnings rank	Avg. return (%)	St. dev. returns (%)	*t*-values	Sharpe ratio
VW	1 (Low)	1.32	5.49	5.18	0.17
VW	5 (High)	1.82	5.30	7.41	0.27
VW	5 - 1	0.50	4.50	2.40	0.11
EW	1 (Low)	1.71	5.10	7.24	0.26
EW	5 (High)	2.03	5.03	8.72	0.33
EW	5 - 1	0.32	2.65	2.63	0.12

Panel B: Summary statistics for returns on industry portfolios excluding industry leaders' earnings announcement date returns

Weight	Earnings rank	Avg. return (%)	St. dev. returns (%)	*t*-values	Sharpe ratio
VW	Bottom 2	1.29	6.48	4.31	0.14
VW	Top 2	1.76	5.84	6.50	0.24
VW	Top 2 - Bottom 2	0.47	7.10	1.42	0.07
EW	Bottom 2	1.56	6.42	5.24	0.18
EW	Top 2	2.03	5.90	7.44	0.28
EW	Top 2 - Bottom 2	0.47	5.80	1.76	0.06

Appendix 7: Earnings seasonalities and stock returns with controls excluding daily returns on one industry leader's earnings announcement dates

For individual stocks: First, I calculate the measure of predicted earnings seasonality, *earnrank*, in quarter q by ranking the 20 quarters of earnings data from the previous five years from largest to smallest and taking the average rank from the previous years of the same fiscal quarter earnings as the upcoming announcement. Second, I predict whether a firm will have an earnings announcement in month t by conditioning on a firm having an earnings announcement 12 months before. Third, I sort all the firms with predicted earnings announcement in month t to quintile portfolios with firms having the highest *earnrank* being in the top quintile portfolio (Q5) and firms having the lowest *earnrank* being in the bottom quintile portfolio (Q1). Fourth, I calculate monthly returns adjusted for intra-industry overreaction for each stock in the sample by excluding the one-day returns from dates when each industry's leader had their earnings announcements. Fifth, I calculate monthly returns for the quintile portfolios. Sixth, I calculate the difference between the top and bottom quintile portfolio to obtain a measure of abnormal returns to earnings seasonalities. Finally, I regress returns of the quintile portfolios and the difference in their returns against the factors in Fama and French (1993) three-factor model and momentum. For industry portfolios: First, I calculate the predicted measure of earnings seasonality, *earnrank*, in quarter q for each stock. Second, I predict whether a firm will have an earnings announcement in month t by conditioning on a firm having an earnings announcement 12 months before. Third, I divide firms in industry portfolios based on 17 Fama-French industries and calculate the value-weighted average *earnrank* for each industry. Fourth, I sort all industries based on *earnrank* and form two portfolios with top-2 industries being in one and bottom-2 industries being in the other. Fifth, I calculate monthly returns adjusted for intra-industry overreaction for the top-2 and bottom-2 portfolios by excluding the one-day returns from dates when each industry's leader had their earnings announcements. Sixth, I calculate the difference between the top-2 and bottom-2 industry portfolios to obtain a measure of abnormal returns to earnings seasonalities. Finally, I regress returns of the top-2 and bottom-2 portfolios and the difference in their returns against the factors in Fama and French (1993) three-factor model and momentum. The calculations use quarterly earnings data as well as monthly and daily stock return data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

Panel A: Four-factor regressions on returns of portfolios formed from individual stocks excluding industry leaders' earnings announcement date returns

Weight	Earnings rank	Four-factor α (%)	*t* -value
VW	1 (Low)	0.70	4.25
VW	5 (High)	1.23	6.69
VW	5 - 1	0.54	2.58
EW	1 (Low)	1.00	7.51
EW	5 (High)	1.38	10.26
EW	5 - 1	0.38	2.96

Panel B: Four-factor regressions on returns of industry portfolios excluding industry leaders' earnings announcement date returns

Weight	Earnings rank	Four-factor α (%)	*t* -value
VW	Bottom 2	0.61	2.48
VW	Top 2	1.22	5.09
VW	Top 2 - Bottom 2	0.61	1.79
EW	Bottom 2	0.86	3.64
EW	Top 2	1.43	6.55
EW	Top 2 - Bottom 2	0.57	2.05

Appendix 8: Earnings seasonalities and stock returns with controls excluding cumulative three-day returns on one industry leader's earnings announcement dates

For individual stocks: First, I calculate the measure of predicted earnings seasonality, *earnrank*, in quarter q by ranking the 20 quarters of earnings data from the previous five years from largest to smallest and taking the average rank from the previous years of the same fiscal quarter earnings as the upcoming announcement. Second, I predict whether a firm will have an earnings announcement in month t by conditioning on a firm having an earnings announcement 12 months before. Third, I sort all the firms with predicted earnings announcement in month t to quintile portfolios with firms having the highest *earnrank* being in the top quintile portfolio (Q5) and firms having the lowest *earnrank* being in the bottom quintile portfolio (Q1). Fourth, I calculate monthly returns adjusted for intra-industry overreaction for each stock in the sample by excluding the three-day returns (t – 1 through t + 1) from dates when each industry's leader had their earnings announcements. Fifth, I calculate monthly returns for the quintile portfolios. Sixth, I calculate the difference between the top and bottom quintile portfolio to obtain a measure of abnormal returns to earnings seasonalities. Finally, I regress returns of the quintile portfolios and the difference in their returns against the factors in Fama and French (1993) three-factor model and momentum. For industry portfolios: First, I calculate the predicted measure of earnings seasonality, *earnrank*, in quarter q for each stock. Second, I predict whether a firm will have an earnings announcement in month t by conditioning on a firm having an earnings announcement 12 months before. Third, I divide firms in industry portfolios based on 17 Fama-French industries and calculate the value-weighted average *earnrank* for each industry. Fourth, I sort all industries based on *earnrank* and form two portfolios with top-2 industries being in one and bottom-2 industries being in the other. Fifth, I calculate monthly returns adjusted for intra-industry overreaction for the top-2 and bottom-2 portfolios by excluding the three-day returns (t – 1 through t + 1) from dates when each industry's leader had their earnings announcements. Sixth, I calculate the difference between the top-2 and bottom-2 industry portfolios to obtain a measure of abnormal returns to earnings seasonalities. Finally, I regress returns of the top-2 and bottom-2 portfolios and the difference in their returns against the factors in Fama and French (1993) three-factor model and momentum. The calculations use quarterly earnings data as well as monthly and daily stock return data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

Panel A: Four-factor regressions on returns of portfolios formed from individual stocks excluding industry leaders' earnings announcement date returns

Weight	Earnings rank	Four-factor α (%)	*t*-value
VW	1 (Low)	0.61	3.62
VW	5 (High)	1.19	6.37
VW	5 - 1	0.58	2.68
EW	1 (Low)	0.97	7.36
EW	5 (High)	1.34	10.05
EW	5 - 1	0.37	2.92

Panel B: Four-factor regressions on returns of industry portfolios excluding industry leaders' earnings announcement date returns

Weight	Earnings rank	Four-factor α (%)	*t*-value
VW	Bottom 2	0.50	2.01
VW	Top 2	1.22	5.18
VW	Top 2 - Bottom 2	0.72	2.12
EW	Bottom 2	0.77	3.25
EW	Top 2	1.43	6.59
EW	Top 2 - Bottom 2	0.66	2.38

Appendix 9: Mutual exclusivity of cross-sectional return seasonalities and earnings seasonalities excluding daily returns on one industry leader's earnings announcement dates

Results for both individual stocks and industry portfolios in Panel A are obtained by regressing the intra-industry overreaction adjusted returns (one-day return, one industry leader) to the same month strategy, the other-month strategy, and their difference in month *t* against earnings seasonality difference portfolio in the same month. Results for both individual stocks and industry portfolios in Panel B are obtained by regressing the intra-industry overreaction adjusted returns (one-day return, one industry leader) to the top portfolio, the bottom portfolio, and their difference in month *t* against return seasonality difference portfolio in the same month utilizing only firms with a predicted earnings announcement in the given month. The calculations use quarterly earnings data as well as monthly and daily stock return data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

Panel A: Return seasonalities after controlling for earnings seasonalities and industry leaders' earnings announcement date returns (same-month and other-month average returns calculated from monthly returns adjusted for industry leaders' earnings announcement date returns)

	Sort by											
	Same-month return				Other month return				Same - other			
Set of assets	α (%)	*t*-value	*b* (%)	*t*-value	α (%)	*t*-value	*b* (%)	*t*-value	α (%)	*t*-value	*b* (%)	*t*-value
Individual stocks	0.93	4.06	-1.65	-0.31	-0.97	-4.34	-11.23	-2.21	1.90	6.45	9.58	1.42
Industry portfolios	0.55	2.41	4.43	1.36	-0.25	-1.04	-0.51	-0.15	0.80	2.42	4.94	1.05

Panel B: Earnings seasonalities after controlling for return seasonalities and industry leaders' earnings announcement date returns (same-month and other-month average returns calculated from monthly returns adjusted for industry leaders' earnings announcement date returns)

Set of assets	Earnings rank	α (%)	*t*-value	b (%)	*t*-value
Individual stocks	1 (Low)	1.51	6.02	-9.47	-3.84
	5 (High)	1.89	7.56	-1.09	-0.44
	5 - 1	0.38	1.90	8.39	4.28
Industry portfolios	Bottom 2	1.41	4.84	-6.93	-2.39
	Top 2	1.81	6.51	-1.99	-0.72
	Top 2 - Bottom 2	0.39	1.21	4.94	1.53

Appendix 10: Mutual exclusivity of cross-sectional return seasonalities and earnings seasonalities excluding cumulative three-day returns on one industry leader's earnings announcement dates

Results for both individual stocks and industry portfolios in Panel A are obtained by regressing the intra-industry overreaction adjusted returns (three-day return, one industry leader) to the same month strategy, the other-month strategy, and their difference in month *t* against earnings seasonality difference portfolio in the same month. Results for both individual stocks and industry portfolios in Panel B are obtained by regressing the intra-industry overreaction adjusted returns (one-day return, one industry leader) to the top portfolio, the bottom portfolio, and their difference in month *t* against return seasonality difference portfolio in the same month utilizing only firms with a predicted earnings announcement in the given month. The calculations use quarterly earnings data as well as monthly and daily stock return data from November 1978 through September 2017 for NYSE, Amex, and NASDAQ stocks.

Panel A: Return seasonalities after controlling for earnings seasonalities and industry leaders' earnings announcement date returns (same-month and other-month average returns calculated from monthly returns adjusted for industry leaders' earnings announcement date returns)

	Sort by											
	Same-month return				Other month return				Same - other			
Set of assets	α (%)	*t*-value	*b* (%)	*t*-value	α (%)	*t*-value	*b* (%)	*t*-value	α (%)	*t*-value	*b* (%)	*t*-value
Individual stocks	0.88	3.88	-2.48	-0.50	-0.78	-3.61	-12.15	-2.55	1.66	5.91	9.67	1.56
Industry portfolios	0.40	1.89	3.43	1.15	-0.21	-0.94	-0.60	-0.19	0.61	2.12	4.03	1.00

Panel B: Earnings seasonalities after controlling for return seasonalities and industry leaders' earnings announcement date returns (same-month and other-month average returns calculated from monthly returns adjusted for industry leaders' earnings announcement date returns)

Set of assets	Earnings rank	α (%)	*t*-value	b (%)	*t*-value
Individual stocks	1 (Low)	1.44	5.71	-9.72	-3.88
	5 (High)	1.83	7.40	-1.27	-0.52
	5 - 1	0.39	1.89	8.44	4.13
Industry portfolios	Bottom 2	1.34	4.49	-7.66	-2.60
	Top 2	1.77	6.53	-2.00	-0.75
	Top 2 - Bottom 2	0.43	1.31	5.66	1.74